USING MULTISPECTRAL AERIAL IMAGERY AND GIS-BASED APPROACHES TO QUANTIFY JUVENILE SALMON REARING HABITAT IN THE KULUKAK RIVER, ALASKA

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A

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Abstract

Monitoring the quality and quantity of freshwater rearing habitat for Pacific salmon *Oncorhynchus* spp. is essential for maintaining stocks of these species. Because field-based habitat monitoring in remote areas can be expensive, time-consuming, and/or subjective, new methods are desired. The objectives of this study were (1) to develop methods for using multispectral aerial imagery to classify juvenile rearing habitat and determine the accuracy of these methods and (2) to use these methods to quantify and map juvenile salmon habitat characteristics in two study areas in the Kulukak River, Alaska. I demonstrated that a decision-based fusion approach using images acquired in the visible, near-infrared, and thermal-infrared regions classified habitat classes important for juvenile salmon with accuracies of 82.5% and 67.5% in the respective study areas. In addition, I quantified and mapped habitat variables often used in juvenile salmon studies on several scales and created habitat-suitability maps for coho salmon *O. kisutch*, demonstrating that both my study areas differed in habitat quantity and quality and are most likely low-quality rearing areas. This study demonstrates that airborne images can be used to determine the quality and quantity of juvenile Pacific salmon rearing habitat in small streams and thus decision support in fisheries management.

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Chapter 1: General introduction

1.1 Introduction

Healthy in-stream habitat has universally been recognized as important for maintaining self-sustaining stocks of Pacific salmon *Oncorhynchus* spp. Further, cataloging, assessing, and monitoring the quality and quantity of available rearing habitat is an important objective for many agencies involved in managing and conserving salmon stocks (Larsen et al. 2004). Both researchers and managers have begun to look at the possibility of both life-history and ecosystem-based approaches to salmon management, and the freshwater habitat component of this is crucial (e.g., Nickelson and Lawson 1998; Sharma and Hilborn 2001; Scheuerell et al. 2006). In addition, climate-driven and human-induced changes in water temperature and availability has the potential to bring about large-scale impacts on the quality and quantity of freshwater habitats available to Pacific salmon during the spawning and rearing life stages (Regier and Meisner 1990; Northcote 1992; Battin et al. 2007; Ficke et al. 2007). Without long-term freshwater habitat monitoring plans, agencies will be unable to adequately develop or maintain ecosystem-based management objectives nor detect climate-induced changes in available spawning and rearing habitat.

Juvenile rearing habitat is especially important to monitor because it provides refuge for a vulnerable life stage for Pacific salmon. It has been recognized that quantity of juvenile rearing habitat is a limiting factor in salmon production (e.g., Nickelson et al.

1992a). Higher quality and quantity of habitat has been shown to increase juvenile production and survival (Beechie et al. 1994; Quinn and Peterson 1996; Solazzi et al. 2000; Ebersole et al. 2009), and several researchers have developed or used carrying-capacity models based on both habitat quality and quantity (Marshall and Britton 1990; Nickelson et al. 1992b; Bradford et al. 1997; Nickelson 1998; Bradford 1999; Bradford et al. 2000; Sharma and Hilborn 2001; Anderson and Hetrick 2004; Nemeth et al. 2004; Anderson 2007).

Researchers have used habitat variables on all scales to predict and explain juvenile Pacific salmon abundance. Watershed-scale variables, including gradient, valley confinement, drainage area, river length, and discharge, have been investigated as a means of describing juvenile density (Bradford et al. 1997; Sharma and Hilborn 2001; Burnett et al. 2007, Wissmar et al. 2010). The literature on reach-scale variables that effect juvenile salmon, including large woody debris (LWD), riparian vegetative cover, substrate composition, habitat complexity, water temperature, water velocity, water depth, channel width, sinuosity, and channel slope, is extensive (e.g., Hillman et al. 1987; Bisson et al. 1988; McMahon and Hartman 1989; Quinn and Peterson 1996; Ebersole et al. 2003; Ebersole et al. 2009). Researchers have also used micro-habitat variables, such as water depth, water velocity, and substrate composition, to explain juvenile salmon preference (Bisson et al. 1988; Taylor 1988; McMahon and Hartman 1989; Bjornn and Reiser 1991; Beecher et al. 2002). Finally, the idea of discrete in-stream “habitat units”, which often encompass some of the above-mentioned reach and habitat variables, have been used to investigate juvenile salmon abundance (e.g., Nickelson et al. 1992b;

Nickelson and Lawson 1998; Anderson and Hetrick 2004; Nemeth et al. 2004; Anderson 2007).

The primary obstacle to traditional salmon habitat monitoring is the associated data collection, which involves classifying fish habitat on spatial and temporal scales that are both large and highly resolute enough be useful for management purposes (Fausch et al. 2002), and can be subjective (Al-Chokhachy and Roper 2010). Watershed-scale variables can be obtained from standard topographical maps, but in remote areas of Alaska, these are often out of date and/or on a crude spatial scale. Although researchers have developed ways of estimating reach-scale and microhabitat habitat quantity without directly measuring habitat features in every section of a watershed, methods such as the basinwide visual estimating technique (BVET; Hankin and Reeves 1988) still involve walking the length of entire watersheds.

Researchers interested in large-scale riverine habitat mapping, especially in remote areas, have begun to recognize the value of remote-sensing applications in solving these problems. Remote sensing has been used to map rivers and streams since the 1930s; since the launch of Landsat in 1972, satellite imagery has allowed for improvements in spectral range and spatial and temporal coverage. Quantification of watershed-scale variables can be improved using satellite imagery (Mertes 2002). However, for in-stream riverine habitat mapping, increased resolution is needed and thus researchers are beginning to explore the possibilities of using low-flying airplanes equipped with cameras capable of collecting multispectral, hyperspectral, and thermal digital imagery. These techniques have allowed for the collection of data that is high-resolution, multi-banded, and easily used by Geographical Information Systems (GIS) based computer software.

Multispectral imagery operates by recording the spectral reflectance at specific wavelengths across the electromagnetic spectrum. Because spectral reflectance of shallow water areas depends on water column depth, substrate albedo, and surface roughness, multispectral and hyperspectral digital imagery has been tested in characterizing riverine habitat through depth and morphology measurements (Winterbottom and Gilvear 1997; Roberts and Anderson 1999; Marcus et al. 2003; Fonstad and Marcus 2005; Legleiter et al. 2009), LWD mapping (Marcus et al. 2003; Smikrud and Prakash 2006; Smikrud et al. 2008), substrate size (Carbonneau et al. 2004; Carbonneau et al. 2005), and habitat unit delineation (Wright et al. 2000; Legleiter et al. 2002; Marcus 2002; Whited et al. 2002a; Whited et al. 2002b; Marcus et al. 2003; Leckie et al. 2005; Gilvear et al. 2007; Marcus and Fonstad 2008). In addition, thermal imagery, which can identify radiation in the infrared range of 0.9-14 µm and can detect temperature differences between objects at temperature resolutions of 0.2° C, has been used to evaluate salmon temperature preferences (Torgersen et al. 1999) and to separate water surfaces from adjacent banks (Smikrud et al. 2008).

Because the aforementioned studies have demonstrated the ability of researchers to use high-resolution imagery and various image processing techniques to classify various riverine characteristics important for juvenile salmon rearing, the U.S. Fish and Wildlife Service (USFWS) Togiak National Wildlife Refuge (TNWR) wishes to develop similar methods in order to implement long-term monitoring of salmon habitat. In order to begin this process, I seek to address the objectives identified below.

1.2 Justification and objectives

The TNWR was established in Southwest Alaska in 1981 by the Alaska National Interest Lands Conservation Act (ANILCA). The mission of the USFWS requires that the TNWR be managed to conserve fish and their habitats in their natural diversity, and to ensure water quality and necessary water quantity within the Refuge. The TNWR considers conserving salmon and salmon habitat within the TNWR necessary because of the ecosystem value of these species, and because of the economic and cultural importance of these fish to commercial, subsistence, and recreation fisheries in the Bristol Bay region. To address these needs and meet the natural diversity conservation mandate for fish and their associated aquatic habitats, the USFWS proposes the development of methods for large-scale and long-term cataloging and monitoring of salmon rearing habitat within the TNWR. The remote nature of most of the streams and rivers within TNWR necessitates novel approaches not entirely reliant on traditional field-based methods. This thesis will begin to address that need by evaluating the ability of multispectral imagery, in conjunction with remote-sensing and GIS-based techniques, to determine juvenile salmon rearing habitat quality and quantity. Specifically, I wish to accomplish the following two objectives:

Objective 1: To develop methods for using multispectral aerial imagery to classify juvenile rearing habitat types and determine the accuracy of these methods using two study areas on the Kulukak River (Chapter 2);

Objective 2: To use multispectral aerial imagery to quantify and map juvenile salmon habitat characteristics in two study areas on the Kulukak River (Chapter 3).

1.3 Study area

Both objectives involve the use of two separate study areas. Both areas investigated in this study are located within the Kulukak River watershed, which lies entirely within the TNWR (Figure 1.1). The Kulukak River is a fifth-order (Strahler 1964) river that originates in the Wood River Mountains and flows south for 73 km before emptying in Kulukak Bay of Bristol Bay, Alaska. Its watershed encompasses 532 km^2. Historical baseline data for the drainage includes surveys of water chemistry, bathymetry, and fish species presence in its largest lake in 1984 and 1988 (MacDonald 1996) and discharge and temperature readings from a USGS stream gauging station since 1999. In addition, landcover mapping of the area was completed in 2003 (Collins 2003). Several studies and observations by refuge biologists have confirmed the presence of all five species of North American Pacific salmon, Dolly Varden *Salvelinus malma*, rainbow smelt *Osmerus mordax*, Arctic char *S. alpinus*, and whitefishes *Coregonus spp.* (MacDonald 1996; Johnson and Klein 2009; M. Lisac, USFWS, personal communications). Salmon escapement in the drainage has been monitored using aerial surveys by ADFG since 1967 in conjunction with management of the 3-d per week commercial salmon fishery within Kulukak Bay (Jones et al. 2008). A counting tower was operated on the river from 1994-1996 (Price and Larson 1999).

The East Fork study area (Figure 1.1) is a fourth-order river section (Strahler 1964) that is 6.2 river kilometers (rkm) in length with wetted widths ranging from approximately 10 to 30 m. The West Fork study area (Figure 1.1) is located on a third-order stream, is 7.4 rkm in length, and has wetted widths ranging from approximately 5 to 15 m. These study areas were selected because they have been documented in the Alaska Department of Fish and Game (ADFG) Anadromous Waters Catalog (AWC) as rearing areas for juvenile salmon, baseline habitat data had been collected on them in a pilot study in 2009, they differed in size from each other, and because they contained all habitat types that I wished to map. The spatial extent of both study areas was chosen by estimating the maximum number of images that could be processed and analyzed within the given time limit.

1.4 Image data

Both study objectives relied on a data set that involved a single aerial image collection period. Airborne data were acquired on 13 May 2010 to avoid periods of ice and leaf out by deciduous vegetation. Images were acquired under a partly cloudy sky and low wind conditions. Mean river discharge was measured as 390 $m^3\ s^{-1}$ at the U.S.

Geological Survey (USGS) stream gauging station located at the downstream end of the Kulukak River on the day of acquisition.

Nadir aerial photographs were acquired from a USFWS Bushhawk Found aircraft modified to include two vertical camera ports. Three cameras were used during image acquisition. A Nikon D300 digital camera (Nikon, Tokyo, Japan) collected visible (VIS) imagery in the blue (0.45-0.52), green (0.52-0.60 µm), and red (0.63 – 0.69 µm) portion of the electromagnetic spectrum. A Forward Looking Infrared (FLIR) A3200 automation series camera (FLIR, Boston, Massachusetts) was used to collect imagery in a thermal infrared (TIR) broadband (7.5 – 13.0 µm) region. In addition, a Nikon D60 digital camera (Nikon, Tokyo, Japan), adapted to capture three overlapping bands in the near infrared (NIR) range (approximately 0.72-0.85 µm for NIR band 1, 0.72-1.2 µm for NIR band 2, and 0.80-1.2 µm for NIR band3), was also used for image acquisition.

During data acquisition, the aircraft was flown over the study areas at an elevation of 750 m above ground level at a speed of 161 km/h (100 mph) to record the VIS, the NIR, and the TIR images at resolutions of 0.25 m, 0.25 m and 1 m, respectively. Imagery acquisition rates and locations of parallel flight lines were pre-determined to include a 60% bottom and 20% side overlap, and all flight lines were flown in the same direction to maintain consistent sun angle and wind speed. The FLIR A3200 was remotely controlled with ThermaCam Researcher software (FLIR, Boston, Massachusetts) in order to acquire and store images in video mode (30 frames/sec) on a laptop. Nikon Camera Control Pro software (Nikon, Tokyo, Japan) was used to remotely control both the Nikon D60 and the Nikon D300 in order to acquire and store images at a rate of 0.20 frames/sec. A Garmin avionics grade GPS unit (Garmin, Olathe, Kansas), with its time-stamp synchronized with all cameras continuously recorded geolocation during data acquisition.

1.5 Image pre-processing

The TIR images acquired by the FLIR system were initially processed using ThermaCAM Researcher software. The software package has an in-built Modtran code that performs atmospheric corrections on the TIR data using just a few user-supplied parameters such as the flying height, atmospheric temperature, atmospheric humidity, wind speed, and ground temperature of a known identifiable target. The software package also uses an inverted Planck's function to convert recorded spectral radiance to radiant temperature and temperature with adjustable emissivity. During ice-free times prior to leaf-out stage, the study area is relatively monotonous with minimal spatial variation in emissivity. Based on the work of Smikrud et al. (2008), I used a uniform emissivity value of 0.96 for this study. Temperature measurements made in the field on the day of acquisition were used to validate the FLIR derived temperature measurements.

Atmospheric correction of VIS and NIR images require access to radiosonde data at or near the study site. There are very few radiosonde data collection sites in Alaska and none of them occur near the Kulukak River. However sky and wind conditions favored high quality image acquisition in the VIS and NIR regions. Also, it has been noted that standard algorithms for atmospheric correction on VIS and NIR data may create additional error when working with water surfaces (Legleiter et al. 2002; Marcus 2002).

All VIS images were mosaicked using an automated tie-point processing technique in Adobe Photoshop CS5 (Adobe, San Jose, California). Erdas Imagine 9.1 (Erdas, Inc., Norcross, Georgia) was used to georectify the uncontrolled mosaics. This was accomplished by using a manual tie-point selection between 10 low emissivity reflectors measuring 1.5 m x 2.5 m placed in highly visible locations in each study area to serve as ground control points (GCPs; Figure 1.2) and differentially corrected GPS coordinates collected at these GCPs using a Trimble Juno (Trimble, Sunnydale, California). After initial georeferencing, the Erdas Imagine Autosync function was used in addition to more manual tie-point selections to ensure sub-pixel coregistration between all three mosaics. Although it was initially intended to use IKONOS imagery for georeferencing purposes, upon examination of satellite imagery it was determined that using the low emissivity reflectors on uncontrolled mosaics produced imagery with much higher coregistration with other ground measurements (see Chapter 2) necessary to meet the objectives. Mosaics of the West Fork and the East Fork images are shown in Figures 1.3 and 1.4, respectively.

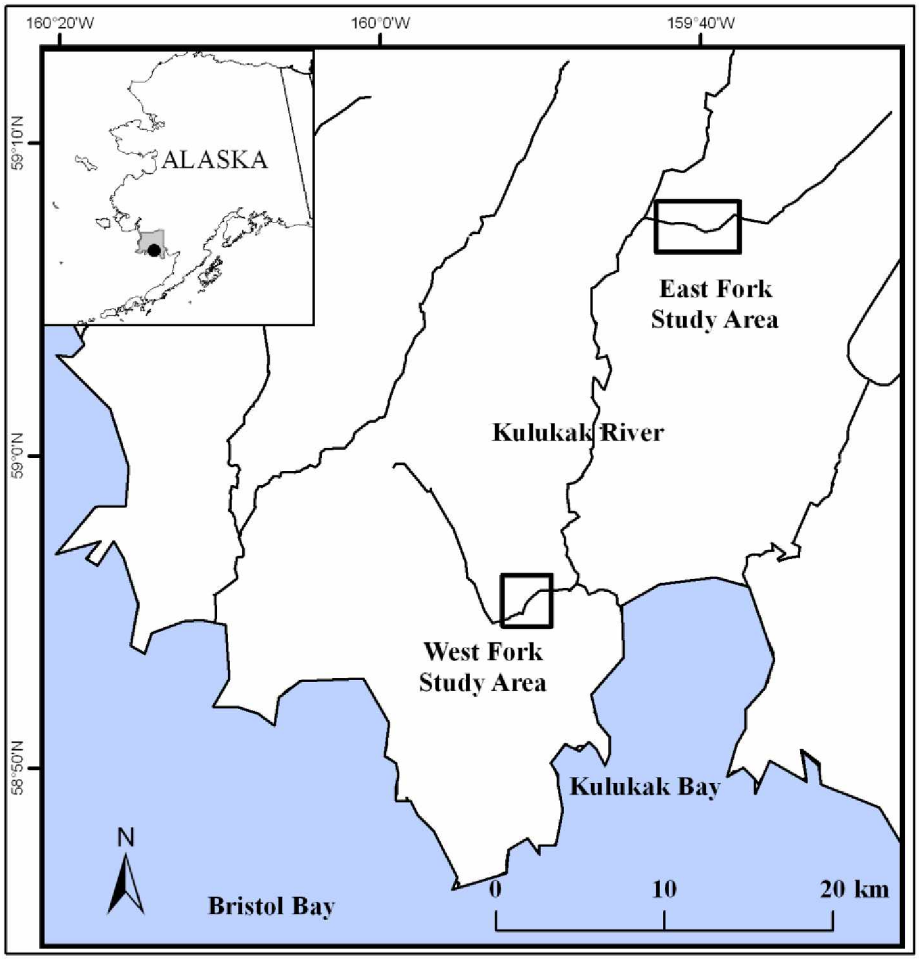

Figure 1.1 The Kulukak River as it flows into Bristol Bay in Southwest Alaska. The East Fork and West Fork study areas are shown in the black boxes and the perimeter of the TNWR is shown in gray in the inset.

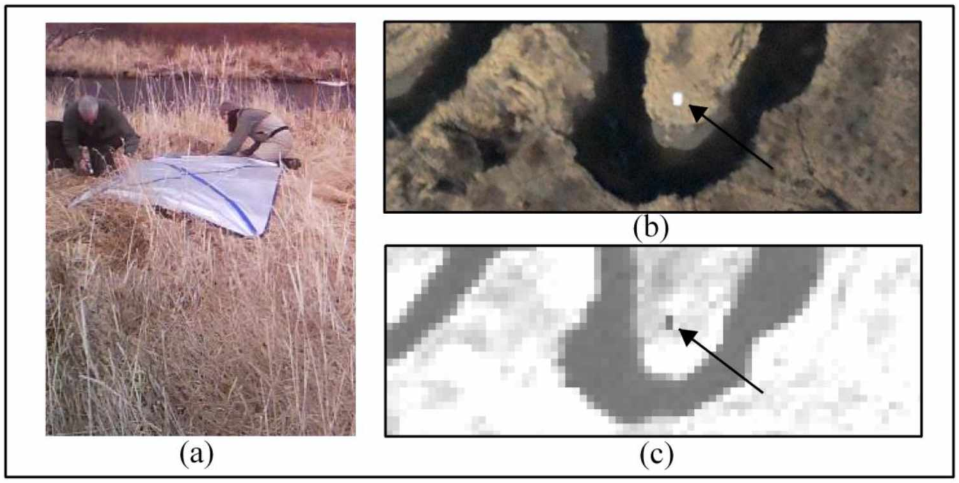

Figure 1.2 (a) Low emissivity reflection blankets were placed throughout the study area as ground control points. These ground control points were highly visible in (b) the VIS image as a bright spot with high digital values, and in (c) the thermal image as a dark spot with very low digital values.

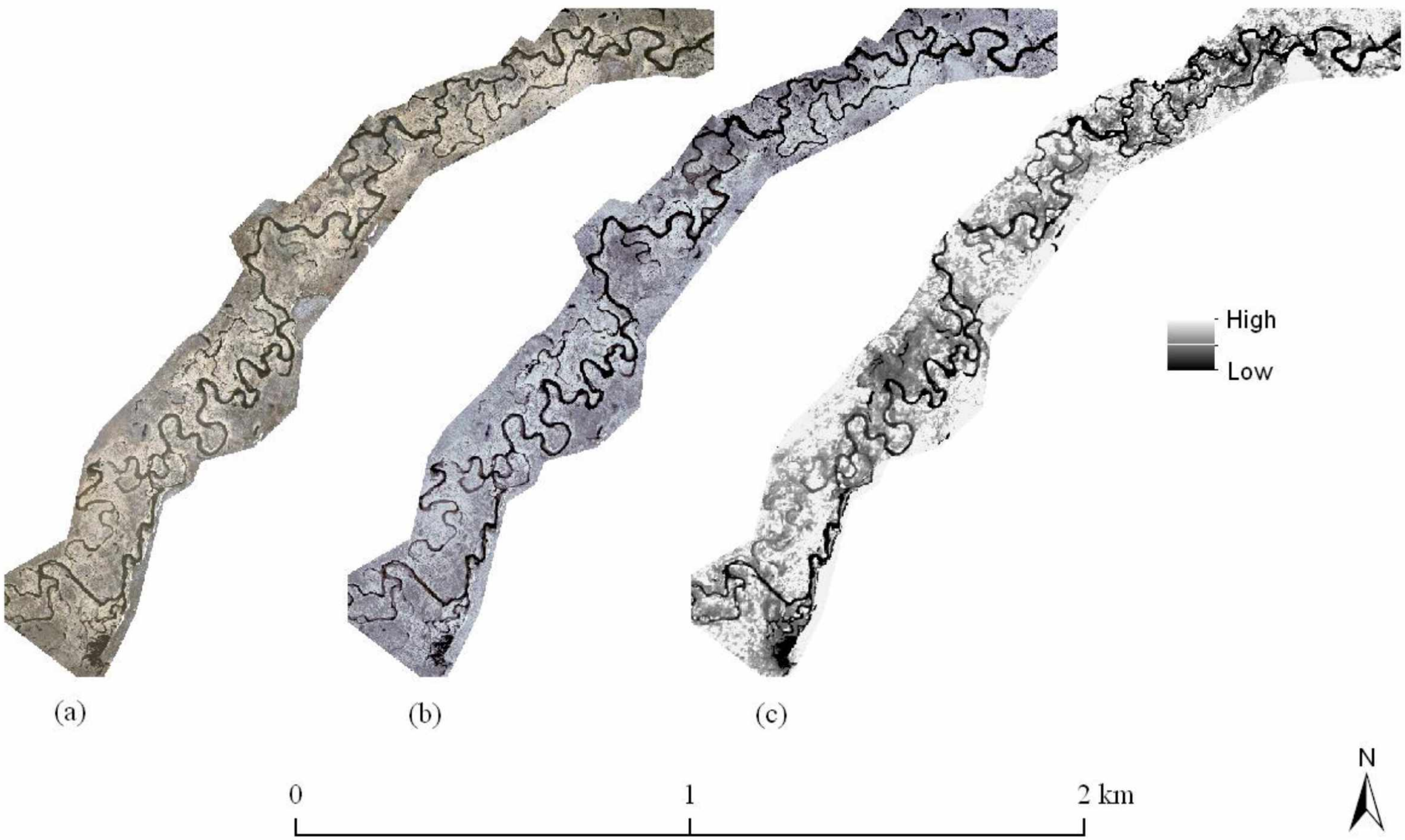

Figure 1.3 The West Fork study area mosaics, as shown in the (a) VIS, the (b) NIR, and the (c) TIR ranges of the electromagnetic spectrum.

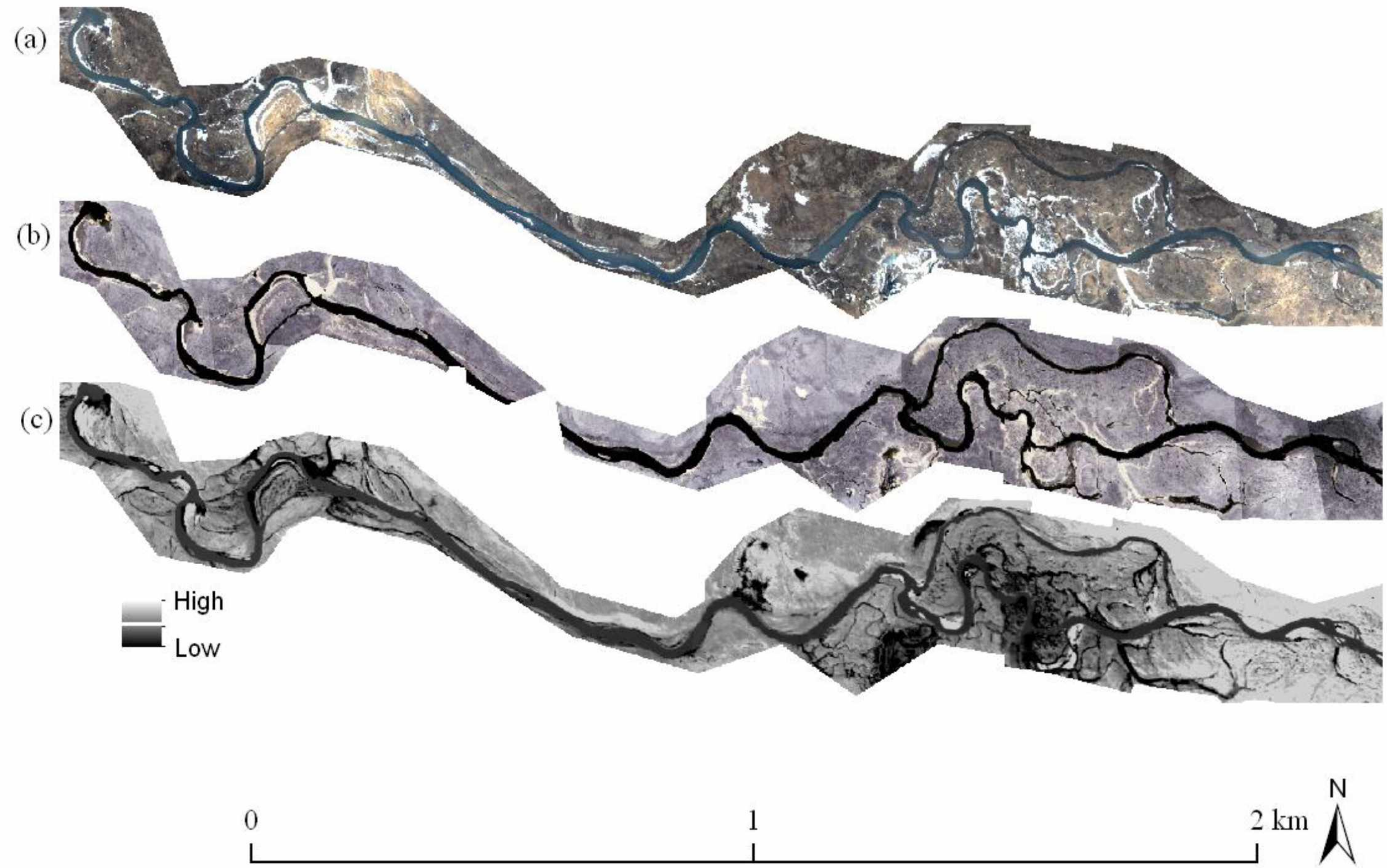

Figure 1.4 The West Fork study area mosaics, as shown in the (a) VIS range, the (b) NIR range, and the (c) TIR range.

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Chapter 2: Determining effective methods for classifying juvenile salmon habitat using decision-based fusion of multispectral aerial photography[1]

Abstract

Monitoring the quality and quantity of freshwater rearing habitat for Pacific salmon *Oncorhynchus* spp. is essential for maintaining stocks of these species. Field-based habitat monitoring in remote areas can be expensive, time-consuming, inaccurate, and/or subjective. I demonstrated the usefulness of high resolution multispectral images acquired in the visible, near-infrared, and thermal-infrared regions in effectively delineating habitat classes important for juvenile salmon rearing in the Kulukak River in Southwest Alaska. This study showed that different spectral bands have complementary strengths, with visible bands being best for delineating main-channel habitats, visible and thermal-infrared for off-channel habitats, and near-infrared for landcover classes. Although no individual classification result captured all the habitat elements, a decision-based fusion that uses selected classes from all classified images provided a product that showed the spatial distribution and quantity of habitat classes. An accuracy analysis using ground-truthed reference data for two separate study areas demonstrated that

[1] Adapted from Woll, C., Prakash, A., and Sutton, T. 2011. A case-study of in-stream juvenile salmon habitat classification using decision-based fusion of multispectral aerial images. Applied Remote Sensing 2:37-46.

habitat classes were identified with accuracies of 82.5% and 67.5%, respectively. Although one study area produced lower accuracies than expected, this study demonstrates that low-cost airborne images can be used to effectively determine the quality and quantity of juvenile Pacific salmon rearing habitat in small streams and thus decision-support in fisheries management.

2.1 Introduction

Freshwater habitat has been long recognized as a limiting factor in Pacific salmon productivity (e.g., Nickelson et al. 1992). This habitat is used not only for spawning by these species, but also as rearing habitat for juveniles, some which spend several years in freshwater before migrating to sea. Because many managers and researchers are interested in implementing ecosystem and life-history based management, as well as respond to the threats of habitat degradation and climate change, cataloging, assessing, and monitoring the quality and quantity of available freshwater rearing habitat is an important objective for many management agencies involved in managing and conserving Pacific salmon *Oncorhynchus* spp. stocks (Larsen et al. 2004).

Several abiotic, reach-scale variables have been universally identified as important in determining the quality of riverine habitat for Pacific salmon rearing potential, including large woody debris (LWD), riparian vegetative cover, substrate composition, habitat complexity, water temperature, water velocity, water depth, channel width, sinuosity, and channel slope, among others (e.g., Hillman et al. 1987; Bisson et al.

1988; McMahon and Hartman 1989; Shirvell 1990; Quinn and Peterson 1996). Categorical habitat units have often been used to supplant the measurement of these habitat features (Bisson et al. 1982; Hankin and Reeves 1988). By mapping and quantifying these habitat characteristics and categorical habitat types, researchers have found a useful way to sample fish and estimate their abundances (Hankin and Reeves 1988).

The primary obstacle to traditional salmon habitat monitoring is the associated data collection, which involves classifying fish habitat on a spatial and temporal scale detailed enough to be useful for management purposes (Fausch et al. 2002) and can also be subjective (Al-Chokhachy and Roper 2010). In many areas of Alaska, monitoring is especially difficult due to the remote nature of the habitat that is most important to salmon populations; for example, most of these areas are only accessible by air. As an alternative to traditional methods, several researchers have demonstrated that remote sensing, and in particular aerial photography, can be used to map and explore freshwater habitat characteristics potentially important for salmon rearing. Multispectral and hyperspectral aerial photography have been used with varying success to classify stream habitat types (Legleiter et al. 2002; Marcus 2002; Whited et al. 2002a; Whited et al. 2002b; Marcus et al. 2003; Leckie et al. 2005; Gilvear et al. 2007b; Marcus and Fonstad 2008), as well as river depth and morphology (Winterbottom and Gilvear 1997; Roberts and Anderson 1999; Fonstad and Marcus 2005; Legleiter et al. 2009), substrate size (Carbonneau et al. 2004; Carbonneau et al. 2005), and LWD (Marcus et al. 2003; Smikrud and Prakash 2006; Smikrud et al. 2008). In addition, thermal infrared (TIR) imagery has also been used to effectively separate water surfaces from adjacent banks (Smikrud et al. 2008), a method that has been suggested as a way to avoid habitat-unit classification errors created by overhead shadows (Leckie et al. 2005).

The aforementioned remote-sensing studies have demonstrated that these image-based methods can provide improvements in accuracy and/or efficiency as compared with field-based sampling, although all studies offer recommendations for improvements. Simple use of visible (VIS) bands may provide useful information about water bodies, but the addition of near-infrared (NIR) bands may provide even more information, especially about other vegetative classes (Smikrud et al. 2008). Hyperspectral collection has thus far proven to be most useful in identifying in-stream habitat classes (Marcus 2002; Marcus et al. 2003). However, hyperspectral systems are expensive and analytically complex, and a system with professional SLR cameras operating in three VIS bands and three NIR bands may serve as an affordable alternative for monitoring remote areas. In addition, the methodologies involving strictly VIS and NIR bands have not yet been used to classify important off-channel habitats such as sloughs and beaver ponds, and have shown consistent misclassifications due to shadow and wet gravel (Leckie et al. 2005). Thus, the incorporation of TIR data has been suggested and used as an approach for extracting water bodies (Leckie et al. 2005; Smikrud et al. 2008), and may assist in classifying slow-moving off-channel habitats. Because these recommendations suggest that no single approach or data set is sufficient, a data-fusion approach (Pohl and van Genderen 1998) provides the opportunity to combine multiple image sources in order to produce an accurate portrayal of juvenile salmon habitat.

2.2 Study objectives

This study builds on the recommendations of earlier researchers to provide effective and affordable methods for collecting and utilizing airborne multispectral images for juvenile Pacific salmon habitat monitoring in areas with difficult access and at scales necessary for detecting change and managing stocks. Specifically, I will map habitat classes often used in traditional salmon habitat studies. The specific objectives of this study are as follows: (1) to establish a data processing strategy for quantifying potential juvenile salmon rearing habitat using a combination of VIS, NIR, and TIR aerial imagery along with a decision-based fusion approach; and (2) to determine the accuracy of this processing technique by applying it to images acquired in two study areas of the Kulukak River and comparing classification results to ground-truthed data.

2.3 Methods

2.3.1 Sample design and reach selection

A one-stage cluster sampling design was used to determine locations for field measurements. Cluster designs have typically been used in remote-sensing error analysis because they provide a cost and time-effective approach to collecting data when mapping large areas (Moisen et al. 1994). A cluster design was appropriate for this study because of constraints due to cost of accessing the remote study areas and the time imposed by seasonal stream discharge changes. In order to determine cluster size, the efficiency analysis described by Moisen et al. (1994) was employed. A cluster size of 100 pixels was chosen as the most efficient in terms of time and cost, based on estimates of the time and cost to move among and between clusters. Because exact pixel placement was not known at time of field collection, study reaches of 10 m in length were used to ensure cluster sizes of a minimum of 100 pixels. Therefore, 10-m reaches represent first-stage clusters in this design, and pixels represent the sampling unit contained within each cluster.

To determine how many reaches would be sampled, the desired confidence, accuracy estimate precision, and time and cost constraints were considered. Using the multinomial sample size formula typically used for error analysis (Congalton and Green 1998), a total sample size of 757 pixels would provide a confidence of 95% and accuracy assessment precision of 0.05 under the assumption of a simple random sample (SRS) for the number of classes I wish to identify. However, because of the nature of the cluster design, intracluster correlation will decrease the precision of these results (Congalton 1988); thus it is desired to collect data on more than 757 pixels. Sample size estimation is highly sensitive to intracluster correlation, which is unknown for these study areas. However, after considering scenarios with a range of possible intracluster correlation values and taking into account the time limit imposed by changing flow conditions as well as the cost of helicopter time, it was decided that 18 reaches should be sampled from each study area. It was hoped that this would allow for high precision given a low intracluster correlation and at least the equivalent of the frequently-cited minimum of 50 pixels per class for SRS (Congalton and Green 1998).

High-resolution (2.5 m) aerial imagery collected of the entire drainage in 1983 and digitized and georeferenced as part of the National Wetland Inventory (NWI; USFWS) was used to determine reach locations within each study area. ArcMap 10.0 (Environmental Systems Research Institution, Inc. [ESRI], Redlands, California) was used for processing this imagery. An unsupervised classification was used to classify pixels from the NWI aerial imagery into water and non-water classes in each study area. Using this classified imagery, wetted edges were delineated and stream centerlines approximated between banks. These centerlines were subdivided into 10-m stream reaches, and eighteen reaches in each study area were randomly selected for the sampling of field measurements.

2.3.2 Field data

All field measurements were conducted within 6 days of imagery acquisition to ensure accurate validation of imagery. Stream gauging data from this time period indicates that discharge did not fluctuate more than 29% during this time period (Figure 2.1). A helicopter was used to transport field crews to all selected reaches.

A Trimble Juno (Trimble, Sunnydale, California) handheld global positioning system (GPS) unit was used to record the location of habitat classes (Figure 2.2) within selected stream reaches. In-stream habitat classes were recorded using the GPS unit as discrete polygons, and included riffles, runs, pools, and eddy-drop zones

(EDZ)/backwater, as used by Marcus (2002) and Marcus et al. (2003) and adapted from habitat-unit types used in many fisheries studies (Bisson et al. 1982). Each of these habitat types are used by juvenile salmon as rearing habitats, and each is associated with different frequencies of use. In addition, the landcover classes of wood, gravel, grass, and ice/snow were observed. Gravel bars were isolated as a class because they help describe active river channels and will change under different flows. Wood refers to the class consisting of all defoliated woody vegetation in the study area, which includes overhanging vegetation and LWD located near and within the water bodies, features that are important in creating fish habitat. Grass areas were identified because they help identify areas of undercut banks, which are frequently used by several species of juvenile salmon. It should be noted that all grass areas during this time period were senescent. The ice/snow class represents an alternative class not essential for fish habitat mapping. Sketches and photographs of selected reaches were produced to supplement GPS measurements. Upon completion of field work, all GPS coordinates were differentially corrected.

2.3.3 Sample site image classification and accuracy assessment

Before processing the entire image mosaic, a sample VIS image (and associated NIR and TIR images) was chosen in order to determine the best processing scheme. The particular sample image was chosen because it encompassed adequate proportions of all the habitat classes I wished to classify (Figure 2.2). All classifications were performed in Erdas Imagine 9.1 (Erdas, Inc., Norcross, Georgia). Classifications were attempted on the following spectral band combinations, as shown in Figure 2.3: 3 VIS bands; 3 NIR bands;

1 TIR band; 3 VIS and 3 NIR bands; and 3 VIS bands and 1 TIR band. All image classifications were performed using supervised classifications with maximum-likelihood probabilities as used in similar studies (Marcus 2002; Whited et al. 2002a; Whited et al. 2002b; Marcus et al. 2003). Representative polygons of each class containing at least 70 pixels were selected as training sets to ensure that the training set statistically represented all spectral classes that I wished to map using a 7-band image stack (Lillesand et al. 2004). The same training set polygons were used for all band combinations.

Because an accuracy assessment (Table 2.1) and visual inspection suggested that no single-band combination produced highest accuracies for all classes, a decision-based fusion approach was also attempted (Figure 2.3). The EDZ/backwater classes produced by the classification of the 4-band image containing VIS and TIR bands and the other landcover classes produced by the classification of the NIR bands were digitally added to the original classification of the VIS bands. This effectively masked areas of wood that had been misclassified as gravel bars in the original classification, as well as off-channel EDZ/backwater areas that had been misclassified as riffles, runs, and pools.

An accuracy assessment of each classified product was completed using standard accuracy assessment practices (Congalton and Green 1998). This accuracy assement is detailed in Appendix A. Expert knowledge of the area was used to create the reference data for the accuracy assessment. A sample of 50 pixels from each class (not including those from training sets) were selected, as this has been suggested as the minimum number required for full analysis (Congalton and Green 1998). Using the reference data, each classified pixel was put into its true category, creating an error matrix. Using this matrix, the user's, producer's, as well as the overall accuracies were computed. User's accuracies represent the proportion of a particular class that is correctly classified according to reference data, whereas the producer's accuracy is the proportion of a particular class in the reference data that is correctly classified (Congalton and Green 1998).

2.3.4 Study area classification and accuracy assessment

Because the decision-based fusion approach was deemed most accurate, as discussed in the Results section, this method was applied to both study areas' image mosaics. An accuracy assessment of each classified mosaic was completed using standard accuracy assessment practices discussed above. However, in this case, field data, in conjunction with expert knowledge of the area, were used to create the reference data for the accuracy assessment. In addition, a Kappa analysis was used to determine a commonly reported Kappa value, which is a measurement of accuracy that is based on the agreement of the error matrix as compared to agreement by chance (Congalton and Green 1998).

2.4 Results

2.4.1 Test image results

Accuracy results for habitat classification on various spectral band combinations are shown in Table 2.1. Initially, classification was attempted on all three bands of the

VIS image, which produced a product with an overall accuracy of 67.8% (Table 2.2). Although the classification appeared to identify main-channel in-stream habitat units well, it misclassified several landcover classes, including wood as gravel bars (user's accuracy: 16.0%). In addition, visual inspection indicates that off-channel EDZ/backwater areas were often classified as other in-stream habitats (producer's accuracy: 43.1%). Classification of three NIR bands provided good classification of landcover classes, with a higher user's accuracy for gravel bars (78.0%), but less accurate in-stream habitat classification. Next, classification was attempted on only the TIR image. This produced poor classification of all classes (overall accuracy: 50.0%), but visual inspection indicated that off-channel areas were warmer than main-channel areas, although they could not be separated using only the thermal band, due to several other landcover areas with temperatures similar to the off-channel areas. Classification of a 6-band image containing all VIS and NIR bands produced less accurate individual classifications for most classes than the independent classifications of the two types of bands, with the exception of higher classification accuracies for runs and grass. Finally, classification of a 4-band image with VIS and TIR bands produced better classification of EDZ/backwater areas (producer's accuracy: 70.9%), and visual inspection indicated that this was due to better classification of off-channel areas. However, all other in-stream classes were classified less accurately than they would have been if the thermal band was not included.

The EDZ/backwater classes produced by the classification of the 4-band image containing VIS and TIR bands and landcover classes produced by the classification of the

NIR bands were digitally added to the original classification of the VIS bands, masking areas of wood that had been misclassified as gravel bars in the original classification, as well as off-channel EDZ/backwater areas that had been misclassified as riffles, runs, and pools. This produced a map with an overall accuracy of 84.3%, which was higher than from any other classification accuracy (Table 2.2). Although runs classified using the 6-band image had higher accuracy than those classified using the VIS image, this was the only in-stream habitat class that was delineated a little bit better by the 6-band image composite. There is high subjectivity in defining the limits of runs in the field and in images (C.Woll, UAF, personal observation). I therefore saw the merit in ignoring this improved classification and instead used the results from the VIS image classification so that all in-stream classes were derived from the same data source. For similar reasons, I used the grass class derived from the 3-NIR band combination for the final fusion product.

2.4.2 Study area results

Results of the accuracy assessment for the West Fork are shown in Table 2.3. Overall accuracy of the decision-based fusion approach was 82.5%, while in-stream habitats classification had an overall accuracy of 76.0%. The Kappa value was estimated as 0.80. The most common misclassifications appear to be EDZ/backwater being misclassified as riffles, and wood being misclassified as gravel bars.

Results of the accuracy assessment for the East Fork are shown in Table 2.4. Overall accuracy of the decision-based fusion approach was 67.5%, and in-stream habitats classification had an overall accuracy of 54.5%. The Kappa value was estimated as 0.63. The most common misclassifications appear to be runs being misclassified as pools or EDZ/backwater areas and ice being misclassified as gravel or riffle areas.

2.5 Discussion

2.5.1 Success of classification

By experimenting with the classification of various bands, it was shown that a fusion approach utilizing classification of all bands in different combinations was the most effective for classifying all eight classes. Overall accuracy of the West Fork study area was found to be 82.5%, which is just below the 85% threshold suggested by some in the remote-sensing community as appropriate for classification use (Foody 2002). In-stream habitat classes (e.g., riffles, runs, pools, and EDZ/backwater) had a lower overall accuracy than the other landcover classes, but reflect perceived natural patterns in habitat distribution (personal observation, 2010). However, overall accuracy of the East Fork study area was much lower, at 67.5%, and although the map produced seems to reflect natural patterns in habitat distribution, it appears as though there is misclassification between run and pool classes, as well ice/snow areas being classified as other classes.

Main-channel, in-stream habitats were best classified using the three VIS bands. Visible wavelengths are capable of penetrating water surfaces (Lillesand et al. 2004), so it is not surprising that these bands are often used in separating water depths and deep-water substrate (Winterbottom and Gilvear 1997; Roberts and Anderson 1999). Because water depths and substrate material are the primary factors determining the differences between runs, pools, and main-channel EDZ/backwater classes on the ground, VIS bands are useful for classifying in-stream habitat units (Legleiter et al. 2002; Marcus 2002; Whited et al. 2002a; Whited et al. 2002b; Marcus et al. 2003). Accuracy results for these in-stream habitats in the West Fork study area are comparable with other similar studies (Legleiter et al. 2002; Marcus 2002; Whited et al. 2002a; Whited et al. 2002b; Marcus et al. 2003; Leckie et al. 2005; Gilvear et al. 2007b; Marcus and Fonstad 2008) despite the fact that only the three VIS bands were used, as opposed to the multi- and hyper- spectral approaches of these other studies. Riffles had the lowest user's accuracy in the West Fork study area, and this appears to be due to sun reflection off smooth water surfaces producing a similar appearance to a turbulent water surface.

The nature of visible wavelengths also sheds some light on why the overall accuracy of the East Fork study area was much lower than the West Fork study area. In general, most sunlight will be absorbed by clear water within about 2 m of the surface; however, absorption in the visual portion of the spectrum depends entirely on the characteristics of the water, which can include turbidity, surface texture, sediment load, and salinity (Lillesand et al. 2004). Researchers interested in mapping river depths using aerial imagery have often found that depth estimates over 0.6 m are much less accurate than those in shallow streams (Winterbottom and Gilvear 1997; Gilvear et al. 2007a). The East Fork study area was not only much deeper than the West Fork study area, with runs deeper than 1.0 m, but also consistently featured a rougher surface due to high velocities (personal observation, 2010) and more illumination differences within the study area . In the West Fork study area, differences in depth were clearly what distinguished runs from pools spectrally, as runs were consistently shallower than pools. However, these differences are not as apparent in the East Fork area, most likely due to depth, light conditions, and surface roughness, and thus runs and pools were often misclassified as each other. These techniques may be more appropriate for shallow streams on days with large amounts of available sunlight.

No studies to date have focused on classifying small off-channel, backwater areas such as sloughs, side channels, and beaver ponds. Because these habitats are particularly important to some species of juvenile salmon, especially coho salmon *O. kisutch* (e.g., Nickelson et al. 1992; Pollock et al. 2004) and because these habitats were present in our study area, I sought to include these areas in our EDZ/backwater class. This class is typically defined by slow to non-existent water velocity, a characteristic not directly derived from remote-sensing data, and fine, lightly colored substrate. Although this uniquely colored fine substrate was easily detectable in the shallow, main-channel portions of our study areas, many of our off-channel habitats, including sloughs and beaver ponds, were too deep for this substrate type to be visible. The TIR imagery was originally included for delineating water bodies and eliminating the influence of shadow but this imagery provided far more useful in its classification of off-channel habitats. Because these off-channel areas received much less flow, they were consistently warmer than main-channel habitats. Thus, with the addition of the VIS bands, which provided necessary distinction between water bodies and warm landcover classes, the TIR band was successful in classifying off-channel EDZ/backwater class.

It has been found in other studies that in the VIS bands there is often spectral confusion between gravel bars, defoliated vegetation, and LWD (Smikrud and Prakash 2006). However, when including bands from the NIR, researchers have been able to distinguish between gravel and wood (Marcus et al. 2003; Leckie et al. 2005), and this agrees with our higher accuracies when classifying these classes using NIR bands. It was apparent that in some cases wood classes were misclassified as gravel bars; clearly some spectral confusion exists even in the NIR region. However, if images were acquired after leaf out by deciduous vegetation, delineation between these classes would be much clearer, although the spectral confusion between defoliated LWD and gravel bars would still be present. One limitation of our NIR sensors was that the spectral band-widths had considerable overlap and therefore resulted in highly correlated data. Truly multispectral NIR bands with non-overlapping wavelength may further improve the classification of wood and vegetated areas.

2.5.2 Limitations and recommendations

Flight direction, sun angle, and light conditions are universally recognized in remote sensing as crucial factors affecting results. In this case, sun glint associated with spectral confusion between riffles and other water classes in the VIS bands may have been avoided under different light conditions. In addition, illumination differences were much more apparent in the East Fork study area, which may explain the lower accuracies in landcover class identification in this study area. Acquiring photographs on days that are either completely clear or completely cloudy may alleviate these problems. Shadow from overhead vegetation, an illumination issue often associated with misclassification in other studies (Leckie et al. 2005; Marcus and Fonstad 2008), was not a large source of misclassification in this study due to minimal levels of vegetative cover.

The designations between in-stream habitat classes are notoriously ambiguous on the ground and in photography (Marcus 2002; Marcus et al. 2003); many of these habitat types possess a fluid transition zone between them, and sometimes are indistinguishable (personal observation, 2010). Pools, runs, and main-channel EDZ/backwater classes are particularly difficult to map on the ground, which explains pixels being wrongly assigned between these classes. Classifications using fuzzy logic may serve as an effective alternative (Legleiter and Goodchild 2005).

In order to address misclassification due to spectral confusion or subjective habitat classes, alternative classification techniques may prove useful. Object-oriented classification, for example, has been used in remote sensing of riverine areas (e.g., Hamilton et al. 2007), and may improve overall accuracy by detecting differences in shape between gravel bars and spectrally-similar wood classes, distinguishing LWD and overhanging cover from other wood areas using in-stream habitat locations, or integrating contextual information about river morphology into in-stream habitat classification.

There is also the possibility that there is seasonal dependence of accuracy in mapping off-channel habitats. In our study, which was carried out in spring, the TIR data was successful in delineating off-channel habitats because of their distinct temperature. However, such distinct class-dependent temperature ranges may not be available during other seasons. In such cases users may need to rely on additional field based measurements, such as water depth and velocities, to aid in improved image interpretation and classification (Whited et al. 2002a; Whited et al. 2002b; Lorang et al. 2005).

Coregistration between ground-truth data and images was not as large an issue in this study as compared with previous research (Marcus 2002; Marcus et al. 2003), which is likely due the advantages gained by using the low-emissivity reflective panels as GCPs, differentially corrected GPS coordinates, and the incorporation of expert knowledge into reference data. However, image-to-image coregistration was most likely a source of errors, and classification errors apparent near class boundaries may be attributed to this problem. A multispectral system operating in the VIS and NIR region, in conjunction with a thermal camera, may provide an efficient alternative. A hyperspectral system that acquires data in the VIS, NIR, and TIR regions may be the most desirable solution, should the price of such a sensor system drop down to a range that makes it affordable for and individual research and resource management agency. Using a true multi- or hyperspectral system could also alleviate the challenges of general spectral confusion and multi-sensor mounting and operation.

2.5.3 Conclusion

In the face of the threats of overfishing, human-induced habitat degradation, and climate change, Pacific salmon and the economies and cultures that rely on them are increasingly vulnerable. Although freshwater habitat research has been long established as a critical component of stock protection and sustainability, current methods of ground-based habitat surveys do not allow for monitoring on a spatial and temporal scale large enough for effective management and change detection, especially in remote areas of Alaska. This study demonstrates how use of airborne remote-sensing data and carefully selected digital image processing and data fusion strategies provide an efficient means of accomplishing what traditional methods cannot, especially in small, shallow streams.

Because bands from the VIS, NIR, and TIR range all contribute significant information in regards to the quality of juvenile salmon rearing habitat, a data-fusion approach is warranted to produce the most accurate representation of actual conditions in salmon streams. It is clear that biologists and managers interested in using these techniques to better monitor and manage salmon populations will need to pay close attention to choice of sensors and conditions under which they choose to acquire aerial images, as well as make crucial decisions about the spatial, spectral, and temporal resolutions needed for their purposes. Regardless of these hurdles, it is clear that remote sensing and data fusion offers a unique opportunity for the fisheries science community to address previous issues concerning the subjectivity and time-consuming nature of juvenile salmon habitat mapping, and to work further toward their goals of managing and conserving Pacific salmon stocks.

Table 2.1 User's and producer's accuracies (%) for each habitat class for classifications of all 5 band combinations and the decision-based fusion (DF) approach as applied on the test image. Results of in-stream habitat classifications are shaded in gray.

	User's accuracies						Producer's accuracies					
	3 VIS	3 NIR	1 TIR	3 VIS + 3 NIR	3 VIS + 1 TIR	DF	3 VIS	3 NIR	1 TIR	3 VIS + 3 NIR	3 VIS + 1 TIR	DF
Riffle	44.0	36.0	12.0	26.0	28.0	56.0	91.7	81.8	85.7	72.2	87.5	96.6
Pool	64.0	40.0	30.0	64.0	66.0	76.0	80.0	66.7	45.5	74.4	78.8	90.5
Run	76.0	80.0	68.0	88.0	82.0	94.0	55.9	47.1	37.8	55.7	48.8	53.4
EDZ	56.0	60.0	66.0	56.0	78.0	68.0	43.1	45.5	46.8	43.8	70.9	82.0
Gravel	16.0	78.0	6.0	18.0	10.0	88.0	88.9	100	50.0	75.0	62.5	100
Wood	92.0	92.0	84.0	86.0	92.0	96.0	48.9	79.3	40.8	52.4	47.9	82.8
Grass	94.0	94.0	60.0	98.0	92.0	98.0	94.0	94.0	56.6	94.0	100	100
Ice	100	100	74.0	100	100	98.0	100	100	100	100	98	100

Table 2.2 Overall accuracy of each classification attempt and for the decision-based fusion approach as applied to the test image.

	Overall accuracy
3 VIS	67.8%
3 NIR	72.50%
1 TIR	50.0%
3 VIS + 3 NIR	67.0%
3 VIS + 1 TIR	68.5%
Data Fusion	84.3%

Table 2.3 Error matrix for the West Fork study area produced by standard accuracy assessment techniques (Congalton and Green 1998).

Classified pixels	Reference pixels								
	Riffle	Pool	Run	EDZ/ backwater	Gravel	Wood	Grass	Ice	Total
Riffle	**26**	0	2	11	1	10	0	0	50
Pool	0	**50**	0	0	0	0	0	0	50
Run	2	9	**36**	3	0	0	0	0	50
EDZ/backwater	2	1	7	**40**	0	0	0	0	50
Gravel	0	0	0	0	**29**	19	1	1	50
Wood	0	0	0	0	0	**50**	0	0	50
Grass	0	0	0	0	0	1	**49**	0	50
Ice	0	0	0	0	0	0	0	**50**	50
Total	30	60	45	54	30	80	50	51	**400**
Producer's	86.6%	83.3%	80.0%	74.1%	96.6%	62.5%	98.0%	98.0%	
User's accuracy	52.0%	100.0%	72.0%	80.0%	58.0%	100.0%	98.0%	100.0%	
Overall accuracy	82.5%								
Kappa coefficient	0.80								

Table 2.4 Error matrix for the East Fork produced by standard accuracy assessment techniques (Congalton and Green 1998).

Classified pixels	Reference pixels								
	Riffle	Pool	Run	EDZ/ backwater	Gravel	Wood	Grass	Ice	Total
Riffle	**26**	0	4	1	2	0	0	17	50
Pool	0	**12**	33	5	0	0	0	0	50
Run	1	3	**46**	0	0	0	0	0	50
EDZ/backwater	1	4	20	**25**	0	0	0	0	50
Gravel	0	0	2	1	**27**	8	0	12	50
Wood	0	0	1	0	0	**49**	0	0	50
Grass	0	0	0	0	0	11	**38**	1	50
Ice	0	0	1	0	0	2	0	**47**	50
Total	28	19	107	32	29	70	38	77	**400**
Producer's	92.9%	63.2%	43.0%	78.1%	93.1%	70.0%	100%	61.0%	
User's accuracy	52.0%	24.0%	9.0%	50.0%	54.0%	98.0%	76.0%	94.0%	
Overall accuracy	67.5%								
Kappa coefficient	0.63								

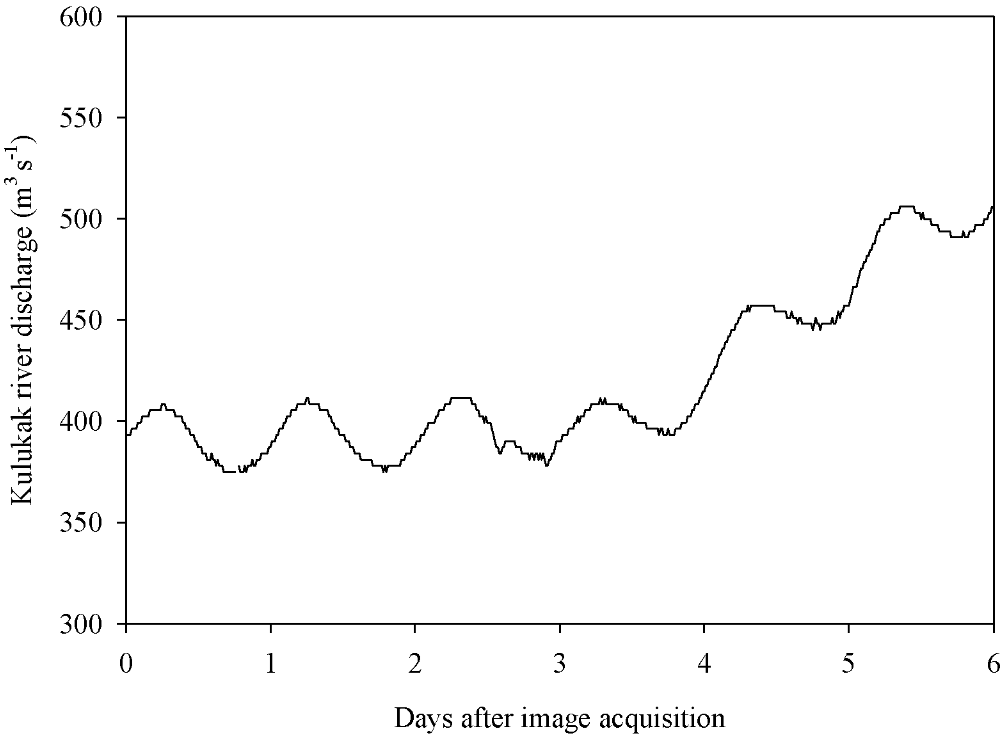

Figure 2.1 Discharge measurements from the USGS Kulukak River stream gauging station for the six days following image acquisition.

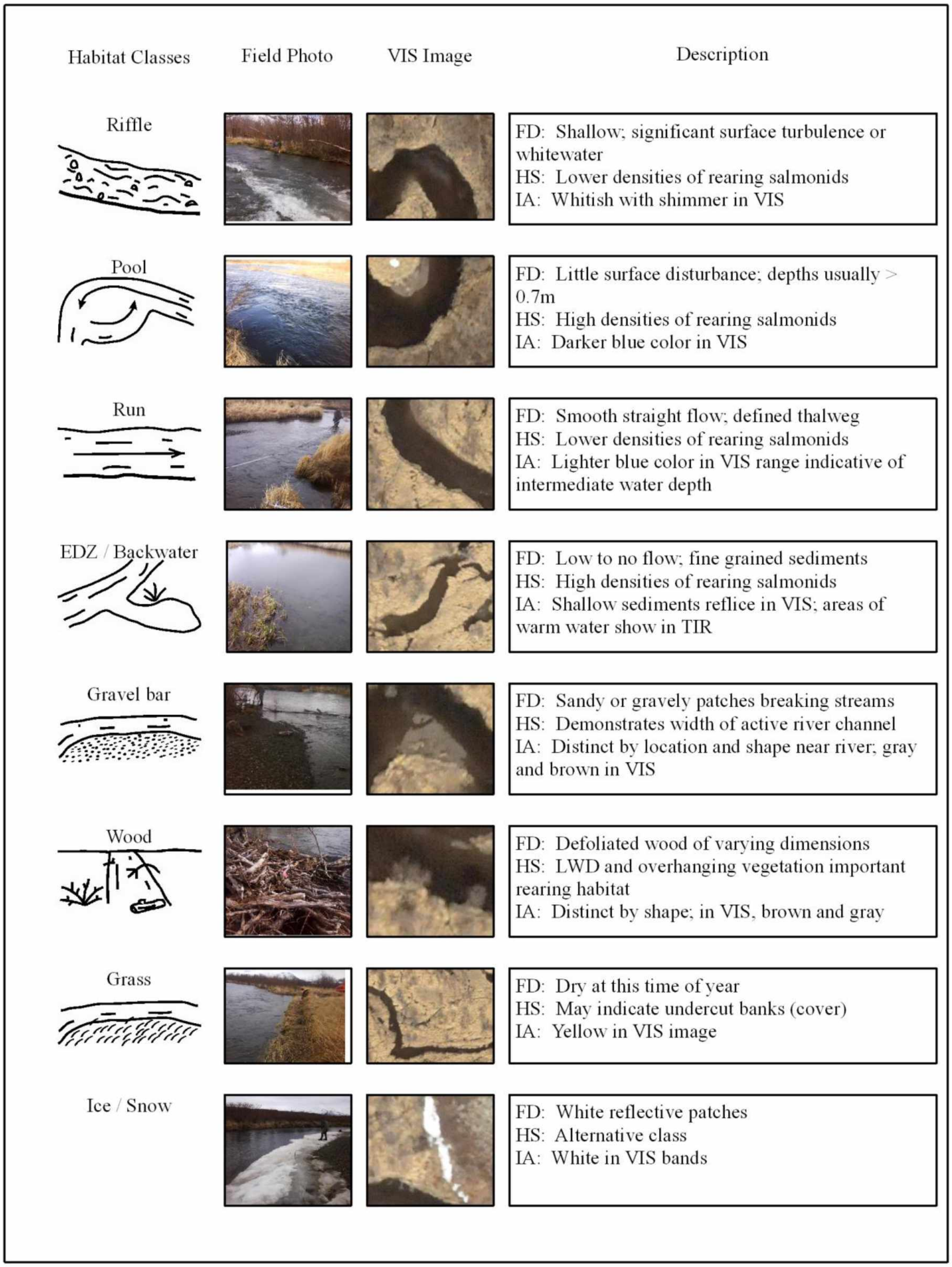

Figure 2.2 Each habitat class used in this study are defined by its field description (FD), its habitat significance (HS), and its image attributes (IA).

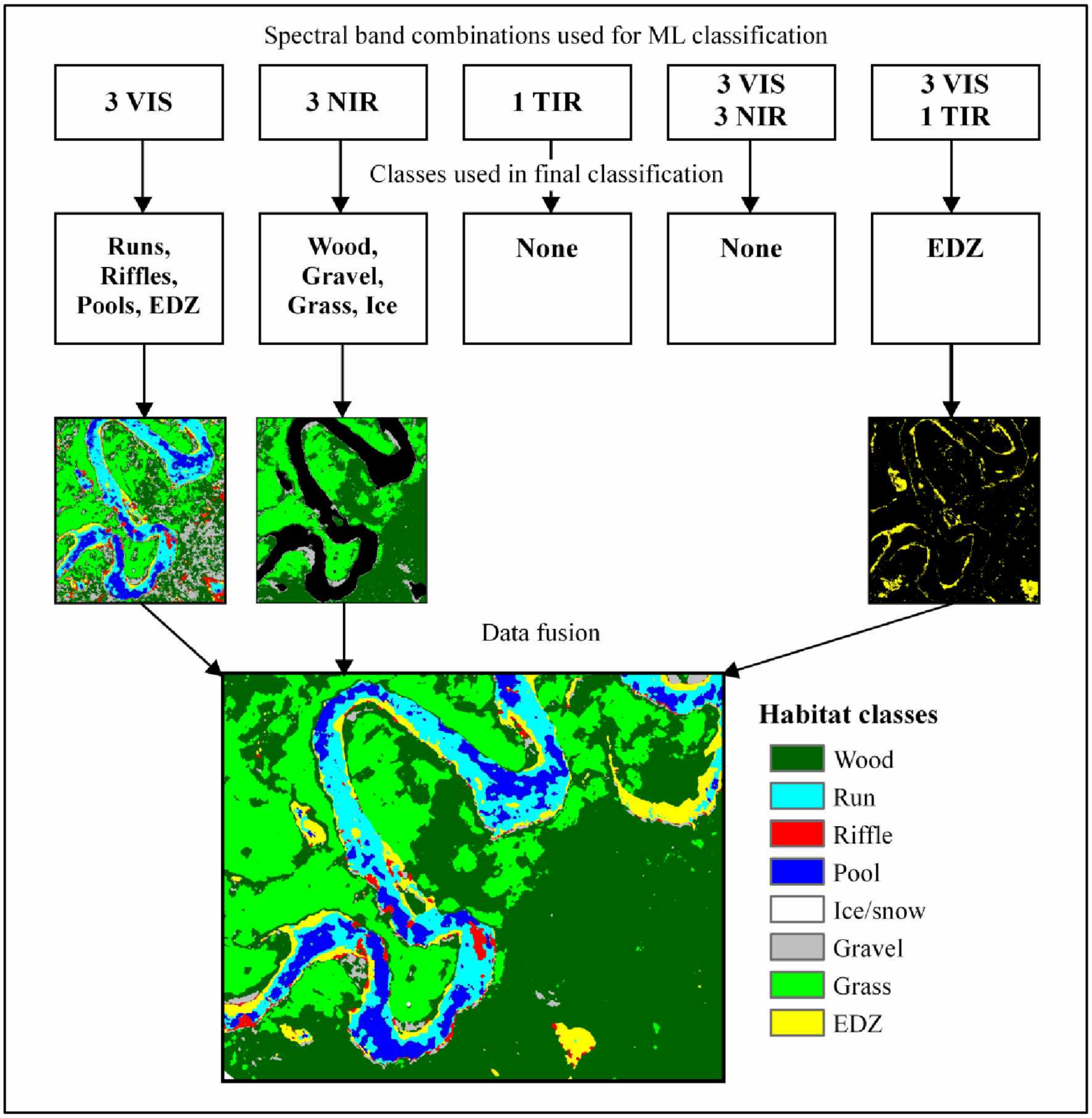

Figure 2.3 Data-processing flow for habitat classification. First, maximum-likelihood classifications were attempted on several different band combinations. Next, the most accurate classes from several different band combinations were extracted. Finally, EDZ/backwater classes produced by the classification of the 4-band image containing VIS and TIR bands and landcover classes produced by the classification of the NIR bands were layered on top of the original classification of the VIS bands to produce a final, fused product.

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Chapter 3: Quantifying and mapping juvenile Pacific salmon habitat on the Kulukak River using multispectral aerial imagery and GIS-based approaches

Abstract

Juvenile rearing habitat is a potentially limiting factor for Pacific salmon *Oncorhynchus* spp. production. Managers thus seek models that incorporate habitat measurements into juvenile salmon abundance estimates. The objectives of this study are to (1) demonstrate that aerial imagery can be used to quantify these habitat measurements on several scales and (2) to compare the habitat quality of two study areas on the Kulukak River using these measurements. My study demonstrates that multispectral aerial imagery and GIS-based techniques can be used to map physically distinct habitat types, quantify habitat variables, and create spatially explicit habitat-suitability maps. I found that East and West Fork study areas differed from each other in habitat quality, with the West Fork containing more backwater areas and the East Fork being composed primarily of run habitats and featuring more pools and cover. A habitat-suitability model for coho salmon *O. kisutch* applied to the classified imagery suggested that both study areas have low suitability for juvenile salmon because they are limited by pool area and/or overhead cover. By using aerial image and GIS-based approaches, researchers and managers can develop spatially explicit predictive models which will improve their ability to manage Pacific salmon stocks.

3.1 Introduction

Healthy in-stream habitat has been universally recognized as important for maintaining self-sustaining stocks of Pacific salmon *Oncorhynchus* spp. Further, cataloging, assessing, and monitoring the quality and quantity of available rearing habitats is an important objective for many agencies involved in managing and conserving salmon stocks (Larsen et al. 2004). Both researchers and managers have begun to look at the possibility of both life-history and ecosystem-based approaches to salmon management, and the freshwater habitat component of this is crucial (e.g., Nickelson and Lawson 1998; Sharma and Hilborn 2001; Scheuerell et al. 2006). In addition, climate-driven and human-induced changes in water quantity and temperature have the potential to bring about large-scale impacts on the quality and quantity of freshwater habitats available to Pacific salmon during the spawning and rearing life stages (Regier and Meisner 1990; Northcote 1992; Bradford and Irvine 2000; Battin et al. 2007; Ficke et al. 2007). Without long-term freshwater habitat monitoring plans, agencies will neither be able to adequately develop or meet ecosystem-based management objectives nor detect climate or human-induced changes in available spawning and rearing habitats.

Researchers have used habitat variables at many scales to predict and explain abundance, habitat preference, and survival of the three species of North American Pacific salmon that overwinter in freshwater: coho salmon *O. kisutch*, sockeye salmon *O.*

nerka, and Chinook salmon *O. tshawytscha* (Fausch et al. 1988). Watershed-scale variables, including gradient, valley confinement, drainage area, river length, and discharge, have been investigated as a means of describing juvenile fish density (Bradford et al. 1997; Sharma and Hilborn 2001; Burnett et al. 2007, Wissmar et al. 2010). The literature on reach-scale variables that effect juvenile salmon, including large woody debris (LWD), riparian vegetative cover, habitat complexity, water temperature, channel width, sinuosity, and channel slope, is extensive (e.g., Hillman et al. 1987; McMahon and Hartman 1989; Quinn and Peterson 1996; Ebersole et al. 2003; Ebersole et al. 2009). Researchers have also used micro-habitat variables, such as water depth, water velocity, and substrate composition, to explain juvenile salmon preference (Bisson et al. 1988; Taylor 1988; McMahon and Hartman 1989; Bjornn and Reiser 1991; Beecher et al. 2002). Finally, the idea of discrete in-stream "habitat units,", which often encompass some of the above-mentioned reach and habitat variables, has been used to investigate juvenile salmon abundance (e.g., Nickelson et al. 1992b; Nickelson and Lawson 1998; Anderson and Hetrick 2004; Nemeth et al. 2004; Anderson 2007). These studies demonstrate that a multi-scale approach may be useful to fully explore juvenile Pacific salmon abundance and habitat preferences.

Traditional approaches to quantifying habitat variables, especially across multiple spatial scales, have several unavoidable flaws. By selecting representative reaches, researchers aim to generalize about the entire river or even an entire watershed (e.g., Hankin 1984). In recent years, this approach has been questioned and, instead, a riverscape approach that seeks spatially continuous data collection has been suggested as an alternative method (Fausch et al. 2002). Unfortunately, collecting data on this scale using ground-based field methods is expensive and time consuming, particularly in remote areas. Traditional field-based methods are notoriously subjective and lack of standardization in field protocols can lead to highly variable or inaccurate data collection and associated management decisions (Al-Chokhachy and Roper 2010).

Remote-sensing approaches, and in particular aerial photography, offer an opportunity to collect data that is spatially continuous, relatively inexpensive, and objective. Research over the past two decades has explored the possibility of detecting and classifying stream features potentially useful for fisheries studies. These features include depth and morphology (Winterbottom and Gilvear 1997; Roberts and Anderson 1999; Marcus et al. 2003; Fonstad and Marcus 2005; Legleiter et al. 2009), LWD and riparian vegetation (Neale 1997; Congalton et al. 2002; Marcus et al. 2003; Smikrud and Prakash 2006; Smikrud et al. 2008), substrate size (Carbonneau et al. 2004, 2005), habitat units (Wright et al. 2000; Legleiter et al. 2002; Marcus 2002; Whited et al. 2002a; 2002b; Marcus et al. 2003; Leckie et al. 2005; Gilvear et al. 2007b; Marcus and Fonstad 2008), and riverine surface water temperatures (Belknap and Naiman 1998; Torgersen et al. 1999, 2001; Madej et al. 2006; Torgersen et al. 2006; South 2010). Although many of these studies have potential fisheries applications, in only a few instances have data obtained from aerial photography been used directly in fishery models (Torgersen et al. 1999; Hedger et al. 2006; Torgersen et al. 2006; Smikrud 2007; South 2010).

3.2 Objectives and justification

This study was conducted to identify methods for cost effective and accurate approaches to providing spatially and temporally continuous data on freshwater Pacific salmon habitat. This study also provided an opportunity to collect baseline data on the quality and quantity of juvenile salmon habitat in two study areas of the Kulukak River, Alaska, located within the Togiak National Wildlife Refuge (TNWR). To accomplish these goals, I have identified the following two study objectives: (1) demonstrate that multispectral aerial imagery can be used to quantify juvenile Pacific salmon habitat variables and create spatially-explicit habitat maps; and (2) describe and compare two study areas of the Kulukak River in regard to their quality of habitat for juvenile Pacific salmon.

3.3 Methods

3.3.1 Data sources

Digital data sources for this study included the mosaicked and georeferenced aerial imagery (see Chapter 1). In addition, I used 30-m resolution Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Map (ASTER GDEM; Alaska Mapped, Fairbanks, Alaska) for all gradient analyses. Field data was collected during the same period as the field data used in Chapter 2. At each 10-m reach that was ground-truthed in Chapter 2, five transects spaced 2.5 m apart were aligned perpendicular to the stream thalweg. At 2.5-m intervals along each transect, coordinates were recorded using a Trimble Juno handheld global positioning system (GPS) unit (Trimble, Sunnydale, California). At each of these points, water velocity and depth were measured using a Flow-Mate 2000 and associated wading-rod (Marsh-McBirney Inc., Frederick, Maryland). All GPS points were differentially corrected after the completion of field work.

3.3.2 Quantifying juvenile salmon variables

Base layer creation

To begin the imagery analyses, I created base layers of water bodies and study reaches. The most efficient way to delineate these water bodies was to classify habitat units first because these habitat classes would be used for later analyses and coregistration between habitat and water delineation was essential. To classify habitats, spectral-based classification methods were used on both mosaics. These methods were detailed in Chapter 2, and had accuracies of 82.5% and 67.5% for the West Fork and East Fork of the Kulukak River, respectively. Eight habitat classes were classified, including four in-stream habitat classes and four landcover classes. In-stream habitat classes included riffles, runs, pools, and eddy-drop zones (EDZ)/backwater. Landcover classes included gravel, wood, grass, and ice/snow. Definitions of these habitat types and their importance to fish habitat are outlined in Chapter 2.

Supervised classifications with maximum-likelihood probabilities were conducted on three-band combinations: three visible light (VIS) bands, three near infrared (NIR) bands, and three VIS bands plus one thermal infrared (TIR) band. Representative polygons of each class containing at least 70 pixels were selected as training sets to ensure that the training set statistically represented all spectral classes that I wished to map using a seven band image stack (Lillesand et al. 2004). The same training set polygons were used for all band combinations. After classification, a decision-based fusion approach was applied, with the EDZ/backwater classes produced by the classification of the four-band image containing VIS and TIR bands and landcover classes produced by the classification of the NIR bands being digitally added to the original classification of the three VIS bands. All classifications and the final fusion were performed in Erdas Imagine 9.1 (Erdas, Inc., Norcross, Georgia).

All following processing was completed using ArcMap 10.0 (Environmental Systems Research Institution, Inc. [ESRI], Redlands, California). To effectively delineate in-stream habitats and overall water areas, ArcMap was used to create new maps by recoding these habitat maps to include only EDZ/backwater, run, pool, and riffle classes. Areas in which LWD or overhanging vegetation were clearly obscuring water bodies were hand digitized as polygons and coded as cover. These maps will hereby be referred to as all-water layers. Another set of maps was created that illustrated only in-stream habitats directly connected (according to classification results) to the main channel; these maps were created by manually deleting water areas with no pixels contiguous to those attached to the main channel. These layers will hereby be referred to as connected water layers.

To delineate study reaches, I also constructed maps of main-channel habitat only. This was done by manually deleting areas that were considered off-channel habitats, defined as areas that had no outlets and whose length was longer than the width of the main channel. Once the main-channel bank lines were established, the ArcMap tool (collapse dual lines to centerlines) was used to create midlines between bank lines. Using these centerlines as thalweg proxies, 100-m reaches were constructed as discrete polygons along the main channel with boundaries perpendicular to the centerlines and coded numerically. These layers will hereby be referred to as reach layers.

Habitat-unit variables and validation

After the aforementioned maps were created, I calculated total area by habitat type for both the original in-stream maps and the in-stream maps with only connected water bodies. I also calculated the number of individual habitat units in each class for both the original in-stream maps and the in-stream maps with only connected water bodies. Next, total areas were calibrated using the classical estimator for statistically calibrating the misclassification bias, proposed by Grassia and Sundberg (1982) and first applied in remote sensing by Prisley and Smith (1987). In this method, final total area estimates were calibrated by multiplying the user's accuracy matrices by the estimated area to produce weight area estimates that reflect misclassification probabilities. The error matrices produced in Chapter 2 for both study areas were used for each respective calculations.

Classified maps were used to enumerate total habitat units by type and calculate proportions by type. Calibrated area estimates were used to calculate habitat proportions by area. This was done for connected waters and non-connected waters.

These four in-stream habitat classes were chosen for their biological significance and their ability to be detected by remote-sensing methods. As a result, I sought to validate the assumptions that they are physically distinguishable units, and thus potentially biologically distinct. Using SigmaStat 3.5 (SYSTAT software, Chicago, Illinois), I used a two-way ANOVA to determine whether depth differed significantly (α=0.05) between study site and habitat-unit type. In addition, I used a two-way ANOVA to determine whether velocity differed significantly (α=0.05) between study site and habitat-unit type. Both depth and velocity values were square-root transformed to comply with normality and equal variance assumptions. When significant differences were found, a Tukey test was used for pairwise multiple comparisons between habitat-unit types.

Stream length and area

To determine stream length, all sections of the centerlines along the main channel were measured. In places where multiple channels were present (ie., braiding) the longest channel was measured (Bain and Stevenson 1999). Using ArcMap, I calculated all-water, connected water, and all main-channel water areas for both study areas. In addition, I calculated water area by reach.

Sinuosity and braiding

To determine the sinuosity of both study areas, I measured the main-channel length and the distance between the upstream- and downstream-most points of each study area. Sinuosity was calculated according to Bain and Stevenson (1999) as the ratio of the main-channel length to the basin length. To determine the braiding index, I began by measuring the total length of all main-channel segments, even those in alternative braids, and length of the widest channel. Braiding was calculated according to Friend and Sinha (1993) as the ratio of the sum of the main-channel lengths to the length of the widest channel.

Elevation and slope

The ASTER GDEM raster was used to determine elevation and slope values. This raster was clipped to the all-water layer, and I calculated the average elevation for all water bodies and the average elevation for each reach. To calculate slope, the relationship used when calculating overall channel slope from USGS topographical maps was used as described in Bain and Stevenson (1999):

Slope = (elevation at 85% - elevation at 10% length) / 0.75 (main-channel length).

Slopes for each reach were also determined by taking the ratio of the difference between the elevations at the upstream and downstream ends of the reach and the reach length.

Cover and riparian vegetation

Total cover area was calculated from the digitized cover layer. In addition, the proportion of water bodies covered was calculated by dividing the total cover area by the total area of water calculated from the all-water polygon layer. I also calculated total cover areas and proportion of water bodies covered by reach. Finally, I applied a 20-m buffer to all reaches and calculated percent riparian vegetation for grasses and deciduous vegetation.

Water depth and associated metrics

To determine if water depth could be estimated from the multispectral imagery, I used a forward stepwise multiple regression procedure in SigmaStat. The digital numbers (DNs) from three visible light (VIS) bands and the three near infrared (NIR) bands were regressed against the linked square-root transformed depth data for each study area separately. The best-fit models were then applied to their respective study area mosaic. I then computed average water depth for all water bodies and by reach and estimated depths were plotted against measured depths.

In addition to water depth, I computed several associated metrics. For each study reach, width-to-depth ratios were computed for each reach by dividing calculated average widths by average depth estimates. Total water volume for each study area, as well as water volume by reach, was calculated by multiplying the depth value of each water pixel by the pixel area.

Water temperature

Water temperature values had already been computed using the automated technique in the ThermaCAM Researcher software (see Chapter 1). Average water temperature was summarized for all water bodies and for individual reaches.

3.3.3 Habitat-suitability maps

To create habitat-suitability maps of the two study areas, I used the Habitat Suitability Index (HSI) methodologies developed by McMahon (1983) for coho salmon. I chose to calculate an HSI for coho salmon because it is the most well studied of the three Pacific salmon species that spend at least a full year in freshwater as juveniles in the Kulukak River and because many of the variables identified as limiting for the juvenile life stage for coho salmon by McMahon (1983) could be quantified using aerial photography in my study. McMahon (1983) identified nine unique variables used to determine the habitat-suitability index for the juvenile life stage of a coho salmon. Five of these variables could be quantified using classified imagery and processing steps detailed above from my study. The original variables of McMahon (1983) as well as modifications that I made to these variables, are detailed in Table 3.1. Using relationships between these variables and habitat suitability developed by McMahon (1983; Table 3.2), a habitat-suitability index between 0 and 1 was calculated for each variable in each study area. The McMahon (1983) model states that the overall habitat suitability is limited by the lowest habitat suitability for a single variable; thus, I calculated the minimum HSI each study area. In addition, I calculated the minimum habitat-suitability index for each reach in each study area.

3.4 Results

3.4.1 Habitat variables

Habitat-unit variables and validation

Classified maps of the Kulukak River serve to demonstrate location and abundance of all in-stream and landcover classes. The West Fork study area contains more grass area than wooded area, and very little ice/snow (Figure 3.1). The East Fork landcover areas consisted primarily of wood, and have more ice/snow areas than the West Fork (Figure 3.2). In addition, there was much more ice/snow in the East Fork than West Fork. The distribution of in-stream habitat types in both study areas often correspond with river features; EDZ/backwater classes tended to be found on river margins and in off-channel areas, runs were located along straight sections of river, pools were found at river bends, and riffles were scattered throughout the reaches. I did not detect trends in the distribution or quantity of in-stream habitat types from upstream to downstream area, although the majority of the riffle class in the East Fork was contained to one small area in the upstream-most section.

Uncalibrated and calibrated total habitat area using the original in-stream habitat maps are showed differences between study areas (Table 3.3). The EDZ/backwater habitat type was the most prominent class in the West Fork, using both uncalibrated and calibrated estimates, followed by runs, pools, and riffles. In the East Fork, runs were the most prominent class, for uncalibrated and calibrated estimates, followed by EDZ/backwater, pools, and then riffles. Individual habitat-unit counts and uncalibrated and calibrated total habitat area counts for both study areas using the in-stream habitat maps of only connected water bodies were similar to previously reported results (Table 3.3). However, there was one exception; the area of runs was greater than EDZ/backwater in the uncalibrated estimates for the West Fork. The EDZ/backwater habitat type was the most abundant habitat unit in the West Fork, followed by riffles, runs, and then pools (Table 3.4). Pools were the most abundant habitat unit in the East Fork, followed by runs, EDZ/backwater, and then riffles (Table 3.4).

Depth as measured in the field was significantly different between habitat types ($F=26.320$, $p<0.001$), but neither study area ($F=0.05$, $p=0.832$) nor the interaction between study area and habitat type ($F=0.729$, $p=0.539$) were significantly different. All habitat-unit types were significantly different in depth from each other with the exception of the EDZ/backwater and riffle comparison (Figure 3.3).

Velocity was significantly different between habitat types ($F=29.045$, $p<0.001$), but not study area ($F=0.220$, $p=0.641$). However, the interaction between study area and habitat type was significant ($F=3.043$, $p=0.038$). In the East Fork, all habitat-unit types were significantly different in velocity from each other with the exception of the run and riffle comparison and the pool and EDZ/backwater comparison (Figure 3.4). In the West Fork, there were only significant differences between EDZ/backwater and all other classes (Figure 3.4).

Calculated habitat variables

I was able to summarize habitat variables at the scales of study area, reaches, and pixels (Table 3.5). Although the West Fork study area was longer, it featured less area water, including connected sections. This study area was more sinuous and more braided than the East Fork, and had a lower average elevation and slightly higher slope. The East Fork had much more cover by wood, and was more than 1°C cooler than the West Fork. This study area was found to be shallower, had less total water volume, and had a higher depth-to-width ratio.

Few trends in measured habitat variables by reach from upstream to downstream exist for either study area (Figures 3.5 and 3.6). However, it appears that quantity of cover decreased from upstream to downstream in the East Fork. In addition, depth, temperature, and water volume increased from upstream to downstream in the West Fork.

Water depth models

For the West Fork study area, a model containing NIR band1, the red band, and the blue band was found to significantly predict water depth ($p<0.001$) as:

$$\text{Depth}^{\wedge 1/2} = 0.475 - 0.00000283(\text{NIR Band 1 DNs}) - 0.0129\ (\text{Red Band DNs}) + 0.0148(\text{Blue Band DNs}).$$

The R^2 between estimated and measured depths was 0.249 (Figure 3.13) and the standard error was estimated at 0.244.

For the East Fork study area, a model containing only the red and blue bands was found to significantly predict water depth ($p<0.001$) as:

$$\text{Depth}^{\wedge 1/2} = 0.615 - 0.00743 \text{ (Red Band DNs)} + 0.00643 \text{ (Blue Band DNs)}.$$

The R^2 between estimated and measured depth was 0.088 (Figure 3.7) and the standard error was estimated at 0.214.

3.4.2 Habitat suitability

Based on the revised McMahon (1983) model, the West Fork study area was limited by the percent pool variable, giving it a minimum HSI of 0.154. The East Fork study area was also limited by the percent pool variable, giving it a minimum HSI of 0.203. In the West Fork, habitat suitability tends to decrease from upstream to downstream, with values ranging from 0.10-0.22 (Figure 3.8). In the East Fork, this trend is reversed, and values range from 0.09 to 0.24 (Figure 3.9).

3.5 Discussion

3.5.1 Quantifying habitat variable using remotely sensed data

This study demonstrates that the habitat-unit types often used in fisheries studies can be successfully classified. The accuracy of my classification techniques was estimated at 82.5% and 67.5% for the West Fork and East Fork, respectively. The difference in accuracy between the two study areas appears to be due to differences in average depths as these techniques should produce more accurate results in shallow (< 1m) streams due to the inability of light to penetrate deep into water bodies (see Chapter 2). Because the area of habitat units have often been used in predicting Pacific juvenile salmon abundance or carrying capacity (Anderson and Hetrick 2004; Nemeth et al. 2004; Anderson 2007) and associated metrics (e.g., pool density and habitat complexity) have been suggested as possible parameters related to juvenile Pacific salmon abundance, mapping these habitats in a spatially continuous manner is valuable for predicting abundance and carrying capacity. The calibration techniques using accuracy results are one possible step toward improving area estimates; however, a more thorough investigation into the accuracy of these techniques may lead to defined precision for these estimates. Although fisheries and riverine researchers often use different categories, language, and definitions when discussing habitat units, it is critical that these discrepancies be amended if consistent methods are sought. For example, the four in-stream classes used in this study are both classifiable in shallow streams using remote-sensing methods and have been shown in my study to be physically different in terms of water depth and velocity, suggesting that they are probably biologically distinct as well. A concurrent juvenile Pacific salmon abundance study in these same areas suggests that these habitat types are associated with different densities of both coho and sockeye salmon (J. Coleman, UAF, unpublished data).

My study also demonstrates that many often-used habitat variables can be obtained using multi-spectral aerial imagery and GIS-based processing techniques. Collecting habitat variables in a spatially continuous and cost-effective way is essential because these variables are useful in predicting fish abundances and monitoring habitat quality (Fausch et al. 1988). Variables that could be used in watershed-scale surveys, including stream length, water area, braiding, sinuosity, elevation, and slope, are all obtainable from imagery and easy GIS-based processing techniques. Currently, these variables are often estimated using USGS topographic maps (e.g., Bradford et al. 1997; Lunetta et al. 1997; Overton et al. 1997; Bain and Stevenson 1999; Burnett et al. 2009). Although using these maps serves as a good first step, they are often low resolution and inaccurate, especially in remote areas. Imagery offers the opportunity to view first-order tributaries and side channels, calculate surface water areas, and track water location and area changes over time, features not often available from topographic maps. These watershed variables could be obtained with lower spectral and spatial resolution than those used in my study. Satellite imagery offers similar advantages as aerial photography in these regards, although the latter allows users more control over spatial and temporal resolution (Lunetta et al. 1997; Burnett et al. 2009).

Reach slope (or gradient) is often cited as an important factor determining geomorphologic properties that frequently determine the quality of fish habitat by regulating such elements as velocity and substrate (Rosgen and Silvey 1996). As a result, gradient is thought to be a factor necessary for predicting juvenile salmon abundance (Fausch et al. 1988; Bradford et al. 1997; Sharma and Hilborn 2001; Burnett et al. 2007, Wissmar et al. 2010). Although the overall slope values for each study area on the Kulukak River give a general sense of the gradient, the fact that some slopes are found to be negative, even though this is not physically possible, makes it is clear that the DEM source (in this case, the ASTER GDEM) is inaccurate, not highly resolute, and/or poorly georeferenced. Although there has been no formal validation of the horizontal accuracy of the ASTER GDEM in Alaska, this data source is estimated to be horizontally accurate within 30 m (ASTER GDEM Validation Team 2009), which is a much lower accuracy than our georeferencing methods and consistently produced root mean square errors (RMSE) under 5 m. Further, validation of the vertical accuracy of the ASTER GDEM had an average accuracy around 20 m at 95% confidence (ASTER GDEM Validation Team 2009), indicating that detecting sub-meter differences in elevation for the purposes of calculating reach slope with this source is most likely inadequate. To better estimate reach-scale gradients, it is suggested that Light Detection and Ranging (LIDAR) data be collected in conjunction with aerial imagery. Light Detection and Ranging data is useful for characterizing riverine geomorphology (Charlton et al. 2003; Jones et al. 2007; Hilldale and Raff 2008). A study by Marchamalo et al. (2008) used LIDAR data to map water depth and velocity in a river in Spain in order to quantify habitat preferred by brown trout *Salmo trutta*, demonstrating the potential of this technology for freshwater fisheries studies.

Cover is an important habitat feature to document when studying juvenile salmon rearing habitat, and has been suggested as an element that provides protection, habitat, and feeding areas for juvenile Pacific salmon during all seasons (Bjornn and Reiser 1991). Several different cover types exist, and each may serve a different function to juvenile Pacific salmon. Root wads and LWD are thought to create in-stream habitat, provide protection from predators, and serve as feeding territories (Bjornn and Reiser 1991), while overhead cover from vegetation may provide shade (and thus, cooler water temperatures; Holtby 1988) and higher densities of terrestrial food sources like insects (Allan et al. 2003). Several aerial photography studies have focused on classifying and quantifying LWD as a separate cover type, and have been successful at doing so either through hyperspectral imagery (Marcus et al. 2003) or spatial filtering of visible light imagery (Smikrud and Prakash 2006). Large woody debris was not distinguishable as a separate cover class in my study for two reasons. First, imagery was acquired before leaf out, making dead wood spectrally indistinguishable from senescent trees and shrubs. This problem could be averted by taking images after leaf out, although this could be problematic if thick cover obscures views of underlying water. Second, the LWD in my study was small and infrequent throughout the river channel. In Smikrud and Prakash (2006), spatial filtering was used to successfully classify LWD. However, the LWD in that study was not only very abundant, but also large and uniquely shaped, being mostly large spruce logs. My study utilized my observations to be able to hand digitize areas of cover, which included all classes of cover. This method is limited in its inability to distinguish between different types of cover and is time intensive. However, estimates of cover using ground measurements as part of a concurrent study suggest that these hand-digitization methods are fairly accurate, with average percentage cover being overestimated by 2% in the East Fork and underestimated by 3% in the West Fork (J. Coleman, UAF, unpublished data).

Undercut banks are another important cover component for juvenile Pacific salmon (Heiftetz et al. 1986; Bjornn and Reiser 1991) that I was unable to quantify using these methods. It is possible that undercut bank presence may be correlated with other data that can be remotely sensed such as particular in-stream or landcover habitat types or river morphology, or it may be a variable that requires ground observation. Portable on-ground LIDAR has not been tested as a means of investigating river morphology, but this method has been used to map 3-dimensional terrestrial systems (e.g., Omasa et al. 2008; Vierling et al. 2008), and a system mounted on a watercraft could potentially evaluate undercut bank presence and size along river corridors during low flow.

Juvenile Pacific salmon have been shown to have depth preferences, and thus mapping water depth can be useful for determining distribution patterns. Riverine water depths have been mapped using aerial photography for several different purposes (Winterbottom and Gilvear 1997; Roberts and Anderson 1999; Marcus et al. 2003; Fonstad and Marcus 2005; Legleiter et al. 2009). My study illustrates that with proper reference data, depth can be estimated to within 0.2 m of its true value in shallow streams; further, depth maps show that, as expected, areas estimated to be deeper are generally found at river bends and confluences, indicating that these maps give at least a good relative measure of depth. However, accuracy drops off significantly after 1 m, contributing to our low correlation between observed and predicted depths. Most sunlight, depending on wavelength, will be absorbed by clear water within about 2 m of the surface, a measure which is dependent entirely on the characteristics of the water (e.g., turbidity, surface texture, sediment load, and salinity; Lillesand et al. 2004). Researchers interested in mapping river depths using aerial imagery have often found that depth estimates over 0.6 m are less accurate than those in shallow streams (Winterbottom and Gilvear 1997; Gilvear et al. 2007a). Our inability to map deep areas and the erroneous finding that the East Fork had a lower average depth than the West Fork (C. Woll, UAF, personal observation) can be attributed to the issues with light absorption, in addition to biased ground sampling, that included only areas that were wadeable, between-image illumination differences, and coregistration issues between data points and corresponding pixels. Other researchers have found correlations as high as 0.97 (Legleiter et al. 2009) when mapping water depths using aerial imagery, and eliminating the problems stated above or including methods such as histogram matching or hyperspectral systems may increase precision and accuracy of these methods in future data collections.

Mapping and monitoring stream temperature has been used to identify potentially lethal temperatures for salmonids and to find groundwater inputs, which may serve as cold-water refugia for juvenile Pacific salmon in summer months or warm habitat in winter months (Power et al. 1999). Thermal aerial imagery has been used in several contexts (including fisheries applications) to map riverine temperatures and identify groundwater inputs (Banks et al. 1996; Belknap and Naiman 1998; Torgersen et al. 1999; Faux 2001; Torgersen et al. 2001; Madej et al. 2006; Torgersen et al. 2006; South 2010). The FLIR imaging and processing software is easy to use and temperatures were estimated to be accurate within 0.2 of measured surface waters. However, in my study, the thermal data provided little information concerning salmon habitat preferences. Because images were taken in the spring, no strong contrast from areas of groundwater input could be detected; thus, potential areas of thermal refugia could not be located. Because water was still cold at this time of year, it was not possible to detect whether there were areas that could be potentially lethal (> 26°C; Bjornn and Reiser 1991) to juvenile Pacific salmon.

3.5.2 Habitat-suitability maps using remotely sensed data

By using the processed aerial imagery, I was able to modify the methods of McMahon (1983) in order to calculate a HSI for the juvenile coho rearing life stage for each reach in each study area of the Kulukak River. These modifications allow for an HSI to be calculated using only the remote-sensing data and processing techniques; however, there are reasons to believe that these modifications may slightly alter the results. McMahon's first criterion, temperature during rearing, actually refers to maximum temperature. This is a criterion that can easily be obtained from FLIR data, but only during the summer months could values high enough to be unsuitable (or even lethal) be detected. Therefore, this criterion may only provide a snapshot in time of the habitat suitability, and therefore should be linked to abundance or monitored during times of the highest water temperatures. The percent canopy criterion, although hand-digitized, appears to be estimated accurately, as overall estimates are similar to those estimated by ground measurements (see above; J. Coleman, UAF, unpublished data). The vegetative composition criterion appears to be accurate due to the high accuracy of classifying deciduous vegetation from grasses (see Chapter 2). The percent pools criterion is assumed to be mostly accurate, especially in the West Fork areas, given the high classification accuracy of the pool class. The proportion of pools criterion may be underestimated because overhanging cover by definition obscures pools below, making it difficult to estimate.

Several of McMahon's (1983) criteria were excluded because they could not be estimated using remote-sensing techniques. Dissolved oxygen has been shown to affect juvenile coho salmon growth, food conversion, and swimming speed (Bjornn and Reiser 1991). In my study areas, dissolved oxygen is assumed not to be a limiting factor due to the fact that these streams are pristine and mostly composed of fast, cool, clear water (C. Woll, UAF, personal observations). No studies to date have looked at determining dissolved oxygen concentration through remote-sensing studies, but as dissolved oxygen levels are associated with turbidity, sediment load, and algal concentrations, it may be possible. Substrate could affect habitat suitability because different substrates correspond with different densities of aquatic invertebrates as food sources (McMahon 1983). However, substrate is assumed not to be a limiting factor in these study areas, and this is supported by substrate-composition estimates produced by habitat surveys by a concurrent study (J. Coleman, UAF, unpublished study). Substrate size has been mapped using aerial photography (Carbonneau et al. 2004, 2005), and extremely high resolution photography could assist in quantifying this criterion. The criterion that includes quantifying in-stream and bank cover was not included because cover located underwater and undercover banks cannot be detected from aerial photography. In-stream and bank cover estimates produced by habitat surveys by the aforementioned concurrent study (J. Coleman, UAF, unpublished data) suggests cover is not limiting according to the McMahon (1983) model; however, a high abundance of juvenile coho associated with undercuts banks in this system (J. Coleman, UAF, unpublished data) may indicate that the use of this habitat is higher than other habitat types compared with that suggested by this model. The winter cover criterion was not included as images were not taken during ice periods, but many have suggested that winter habitat may limit systems such as these (Bustard and Narver 1975; Heifetz et al. 1986; McMahon and Hartman 1989; Nickelson et al. 1992a; Brown et al. 2011). To quantify this criterion in the future, researchers would need to either determine a relationship between habitat such as deep pools and cover in the summer with that in the winter or perform ground surveys during the winter.

It is likely that the McMahon (1983) model is not entirely appropriate for transferring to a system in southwest Alaska; much of the data used to compile this model is based on research conducted in the contiguous United States, and it has been suggested that various differences between systems in Alaska and elsewhere, including climate and seasonal flow regime, may affect the influence of habitat on juvenile salmon (Anderson and Hetrick 2004). Thus, this model is most effective at illustrating the potential of these remote-sensing methods to create spatially explicit habitat-suitability models for juvenile salmon. In practice, however, a more effective alternative to modifying this model, or other models for the other species of juvenile Pacific salmon, would be to create new models based on the capabilities of processed aerial imagery and local ecological data, in conjunction with ground-based methods. Processed aerial imagery offers the opportunity to create habitat-suitability models that are even more spatially explicit than reach-based models, and that are spatially continuous. In recent years, several researchers have begun to explore the possibilities of using data from aerial imagery to assess spatial patterns of fish distribution, and these studies demonstrate the capabilities of these methods to create habitat-suitability maps (Torgersen et al. 1999; Hedger et al. 2006; Torgersen et al. 2006; Smikrud 2007; South 2010).

3.5.3 Potential juvenile salmon rearing habitat in the Kulukak

According to the modified HSI, rearing potential for coho salmon was limited by the percentage of pools for both the East and West Fork of the Kulukak River. The East Fork had a higher HSI (0.203) than the West Fork study area (0.154). According to McMahon (1983), the percentage pool criterion is considered a potential limiting factor because during summer low flow periods, pools provide both access to food and cover from predators, both considered essential to survival. Although no studies have looked at overall productivity of these study areas through smolt enumerations or annual juvenile survival, a concurrent study on juvenile salmon abundance during summer months suggests that juvenile coho salmon utilized EDZ/backwater areas more frequently than pools (J. Coleman, UAF, unpublished data). This suggests that percentage pools may not limit summer production in these areas; however, there is literature to suggest that pools may also limit production in the winter (Bustard and Narver 1975; Heifetz et al. 1986; McMahon and Hartman 1989; Nickelson et al. 1992a; Brown et al. 2011). Further, these study areas may be limited by cover, as both the processed imagery and field data suggests that cover was rarely greater than 20%, including LWD, overhead cover, and undercut banks (J. Coleman, UAF, unpublished data). Physical cover in all forms is recognized as an important habitat requirement for juvenile salmon rearing in freshwater (Bjornn and Reiser 1991), and the lack of cover in these two study areas may make these areas less suitable then other streams in the watershed. All overall and reach-level estimates of HSIs are low, which is supported by density estimates by habitat type for juvenile coho salmon in these two study areas by a concurrent study using removal estimates (J. Coleman, UAF, unpublished data), which are on average lower than those suggested for this species by researchers (Nickelson 1998) and those found in other rivers in southwestern Alaska (Anderson and Hetrick 2004).

The other habitat data collected on these study areas also sheds light on the quality of habitat in these two study areas for all river-rearing juvenile salmon species. The West Fork study area contained a greater abundance of slow-moving waters, including EDZ/backwater areas and pools, which are two habitat types that have been recognized as important for juvenile coho, sockeye, and Chinook salmon summer and winter habitat in previous studies (McMahon 1983; Hillman et al. 1987; Murphy et al. 1989; Reeves et al. 1989; Nickelson et al. 1992a; Nickelson 1998; Rosenfeld et al. 2000;

Sharma and Hilborn 2001; Anderson and Hetrick 2004; Pollock et al. 2004), as well as in a concurrent study in these same study areas (J. Coleman, UAF, unpublished data). However, the West Fork contained very little LWD and overhanging vegetation, which is considered important for river-rearing juvenile coho, sockeye, and Chinook salmon (Bjornn and Reiser 1991). The East Fork, on the other hand, was mostly composed of habitats with faster average velocities, such as runs, which may be more valuable for juvenile Chinook salmon than the other species (Hillman et al. 1987; Murphy et al. 1989; Holecek et al. 2009). However, the concurrent study (J. Coleman, UAF, unpublished data) found very few Chinook salmon in either study area, and it is unknown whether this is due to unsuitable rearing habitat or other factors. The East Fork study area did have more LWD and overhanging cover than the West Fork, but still lower proportions that those preferred by juvenile salmon (Bjornn and Reiser 1991). The range of depths and temperature in both the West Fork and the East Fork contain ranges of preferred depths and temperatures for all three species (Bjornn and Reiser 1991), although examining the spatially continuous maps of these variables provides more useful information on the possible locations of high densities of juvenile salmon.

3.5.4 General conclusion

My study demonstrated that high-resolution aerial imagery can be used to classify physically distinct habitat types in shallow, clear streams. Further, this classified, processed imagery can be effective in determining habitat variables often used in juvenile Pacific salmon abundance and carrying capacity studies under the right environmental conditions. These habitat variables can be summarized at the resolution of study area, reach, and/or pixel. By quantifying these variables in a spatially continuous manner and combining this information with spatially explicit fish surveys, researchers can develop more cost effective and accurate abundance, carrying capacity, and spatially explicit habitat-suitability models.

With freshwater habitat and the fish that rear in these areas potentially being impacted by climate-driven and human-induced changes, it is increasingly important to monitor the quantity and quality of these habitats (Regier and Meisner 1990; Northcote 1992; Bradford and Irvine 2000; Battin et al. 2007; Ficke et al. 2007). My study demonstrated new methods that are both cost effective and informative, and may allow managers to have more access to better information regarding fish distributions and abundances. These data inputs will serve to improve their decision making and ultimately support the goals of conserving and managing Pacific Salmon.

Table 3.1 Variables used by McMahon (1983) to compute the HSI for juvenile coho salmon. Modifications to these variables that I implemented for my models are outlined as well.

Life requisite component	Habitat variable	Description (from McMahon (1983))	Modification
Water quality	Temperature during rearing	Maximum temperature during rearing.	Used average temperature because overhanging vegetation often resulted in inaccurate high maximum temperatures; furthermore, this stream did not come close to reaching the maximum threshold for temperature
	Dissolved oxygen during rearing	Minimum dissolved oxygen concentration during rearing (parr).	Not used; Could not determine this from the imagery or processing techniques; however, it is not assumed to be a limiting factor in this system
	Percent canopy	Percent vegetative canopy over rearing stream.	Included overhanging vegetation and LWD as these are not distinguishable in the images
Food	Vegetation composition of riparian zone	Vegetation index of riparian zone during summer. Vegetation Index = 2 (%canopy of deciduous trees and shrubs) + (% canopy cover of grasses and forbs) + (% canopy cover of conifers).	Calculated as described, with the riparian zone being defined as 20 m from the stream edge
	Percent pools	Percent pools during summer low flow period.	Calculated as percent pool; images were taken during a low-flow period

Table 3.1. continued

	Substrate composition	Substrate composition in riffle/run areas. A. Percent of gravel (10 to 60mm) and rubble (61 to 250mm) present. B. percent fines (< 6 mm) or percent embeddedness of substrate. SI=A+B / 2, where B=% fines or % embeddedness, whichever is lower.
Cover	Percent pools	See previous "Percent pools"
	Proportion of pools	Proportion of pools during summer low flow period that are 10 to 80 m^3 or 50 to 250 m^2 in size and have sufficient riparian canopy to provide shade.
	Percent cover	Percent in-stream and bank cover present during summer low flow period.
	Winter cover	Percent of total area consisting of quiet backwaters and deep (≥ 45 cm) pools with dense cover of roots, logs, debris jams, flooded brush, or deeply-undercut banks during winter.

Not used; could not be determined from imagery or processing techniques.
See previous "Percent pools"
Calculated as pools of that size that have adjacent cover
Not used; bank cover cannot be determined by imagery or processing techniques
Not used; images taken during summer

Table 3.2 Criteria for my habitat-suitability model for juvenile coho salmon. Values are based on those used by McMahon (1983).

Habitat variable	Value ranges	HIS
Temperature during rearing (t)	t < 4°C	HSI = 0
	4°C ≤ t < 8.5°C	HSI = 0.12(t)
	t ≤ 8.5°C	HSI = 1
Percent canopy (c)	c < 20%	HSI = 0.5(c) + 0.2
	20% ≤ c < 40%	HSI = 2.75(c) – 0.25
	40% ≤ c < 50%	HSI = 1.5(c) + 0.25
	50 %≤ c < 75%	HSI = 1
	75% ≤ c	HSI = -2.4(c) + 2.8
Vegetation composition of riparian zone (v)	v < 75	HSI = 0.3(v)
	75 ≤ v < 125	HSI = 0.011(v) – 0.525
	125 ≤ v < 160	HSI = 0.004(v) – 0.31
	160 ≤ v	HSI = 1
Percent pools (p)	p < 20%	HSI = 0.5(p) + 0.1
	20% ≤ p < 30%	HSI = 1.0(p)
	30% ≤ p < 35%	HSI = 12(p) – 3.3
	35% ≤ p < 45%	HSI = 1(p) + 0.55
	45% ≤ p < 60%	HSI = 1
	60% ≤ p < 80%	HSI = -3(p) + 2.8
	80% ≤ p	HSI = -1(p) + 1.2
Proportion of pools (r)	r < 20%	HSI = 0.25(r) + 0.2
	20 %≤ r < 50%	HSI = 0.83(r) – 0.083(r)
	50% ≤ r < 60%	HSI = 4.0(r) -1.5(r)
	60 %≤ r < 75%	HSI = 0.67(r) + 0.5
	r ≤ 75%	HSI =1

Table 3.3 Total habitat area by habitat type for all-water bodies and connected water bodies located within both Kulukak study areas using both uncalibrated and calibrated measures.

	All-water bodies				Connected water bodies			
	West Fork		East Fork		West Fork		East Fork	
	Total (km^2)	Total calibrated (km^2)	Total (km^2)	Total calibrated (km^2)	Total (km^2)	Total calibrated (km^2)	Total (km^2)	Total calibrated (km^2)
EDZ	44.69	38.48	28.59	16.81	27.3	24.32	19.18	11.32
Pool	9.50	15.62	20.12	97.88	90.87	14.69	16.47	81.17
Riffle	4.50	5.29	57.67	44.61	37.21	41.48	41.16	34.00
Run	29.02	27.33	44.54	74.91	28.06	24.17	43.81	59.18

Table 3.4 Number of habitat units, proportion of habitat units, and proportion of total area for both study areas of the Kulukak River.

	West Fork			East Fork		
	# of habitat units	Proportion of habitat units	Proportion of total area	# of habitat units	Proportion of habitat units	Proportion of total area
EDZ	3,300	33.99%	36.12%	2,806	25.31%	13.80%
Pool	1,282	13.21%	21.81%	3,959	35.71%	9.90%
Riffle	2,951	30.39%	6.16%	1,207	11.89%	4.14%
Run	2,175	22.40%	35.91%	3,116	28.10%	72.12%

Table 3.5 Values for all measured habitat variables by Kulukak River study area.

	West Fork	East Fork
Total river length (rkm)	5.47	4.37
Total area water (km^2)	88.17	99.02
Total area connected water (km^2)	59.18	84.92
Basin length (km)	2.35	2.99
Sinuosity	2.33	1.46
Braiding index	1.27	1.21
Average elevation (m)	5.08	42.81
Total slope (%)	0.05	0.04
Total cover by wood (m^2)	464	2,452
Average water depth (m)	0.46	0.37
Average depth-to-width ratio	18.80	38.9
Total water volume (km^3)	40.56	36.64
Average water temperature (°C)	6.57	5.22

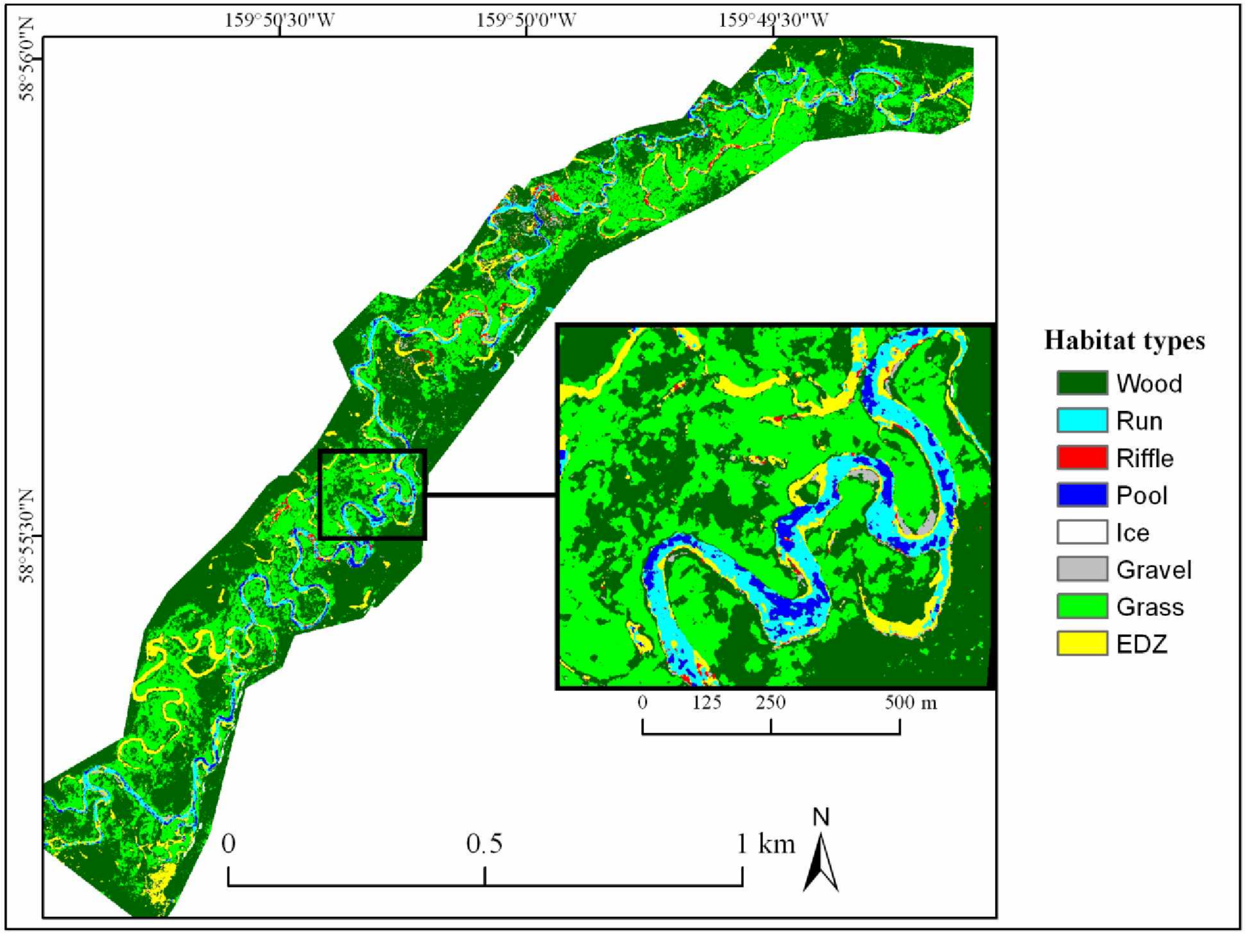

Figure 3.1 The classified mosaic of the West Fork of the Kulukak River study area. This map shows distributions and abundances of all habitat classes and indicates that the West Fork has more EDZ/backwater and grass areas than the East Fork.

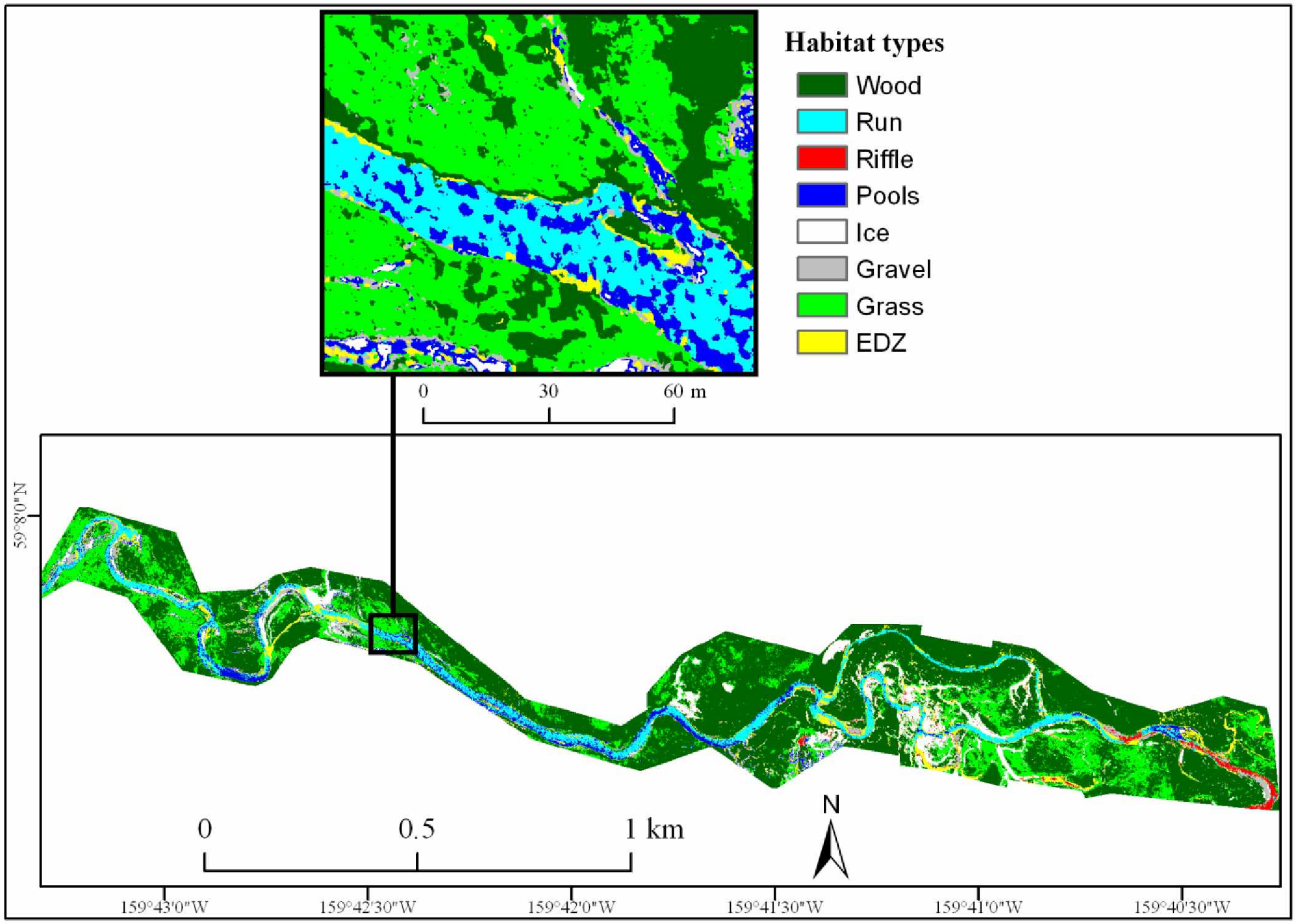

Figure 3.2 The classified mosaic of the East Fork of the Kulukak River study area. This map shows distributions and abundances of all habitat classes and indicates that the West Fork has more run, wood, and ice areas than the West Fork.

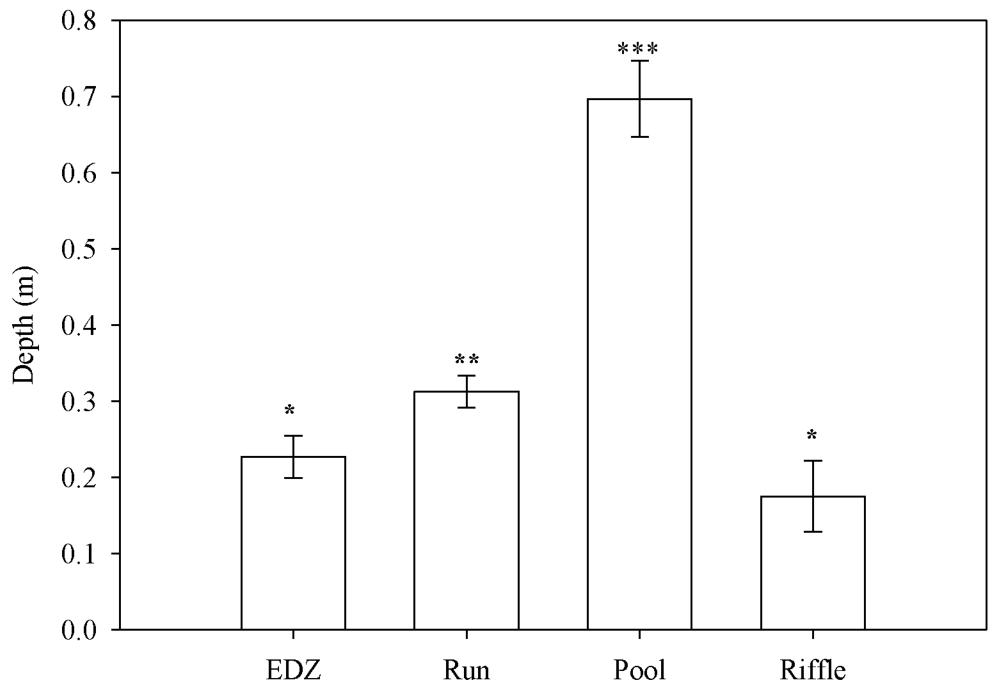

Figure 3.3 Mean water depth (± SE) by habitat type for both study areas of the Kulukak River combined using field data. Habitat types that are significantly different from one another are shown with asterisks ($p < 0.05$).

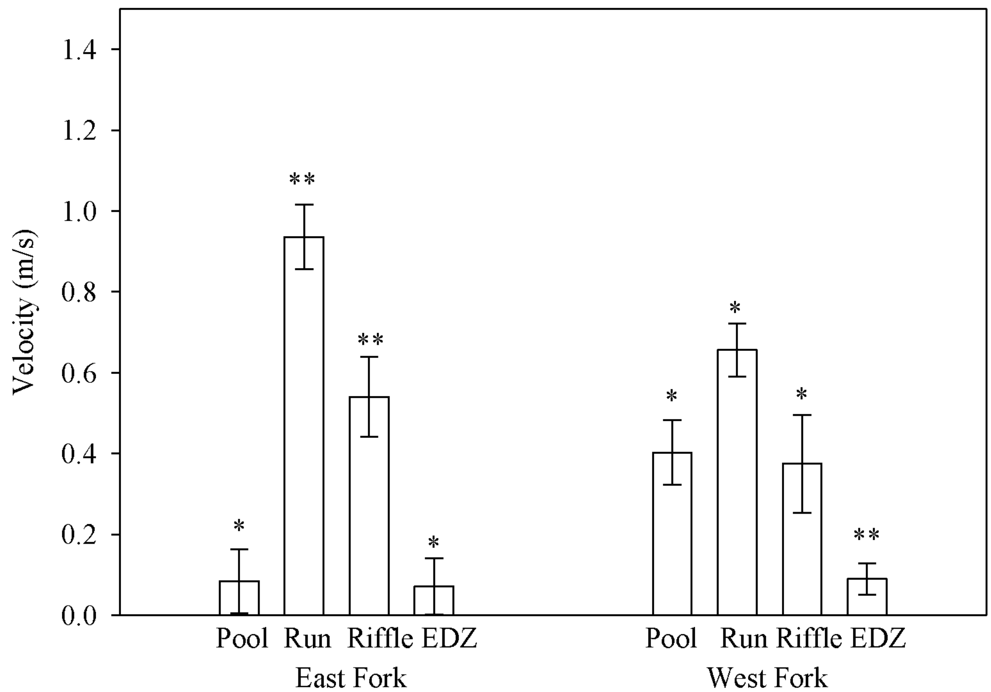

Figure 3.4 Mean water velocity (± SE) by habitat type for both study areas of the Kulukak River. Habitat types that are significantly different from one another in their respective study areas are shown in asterisks.

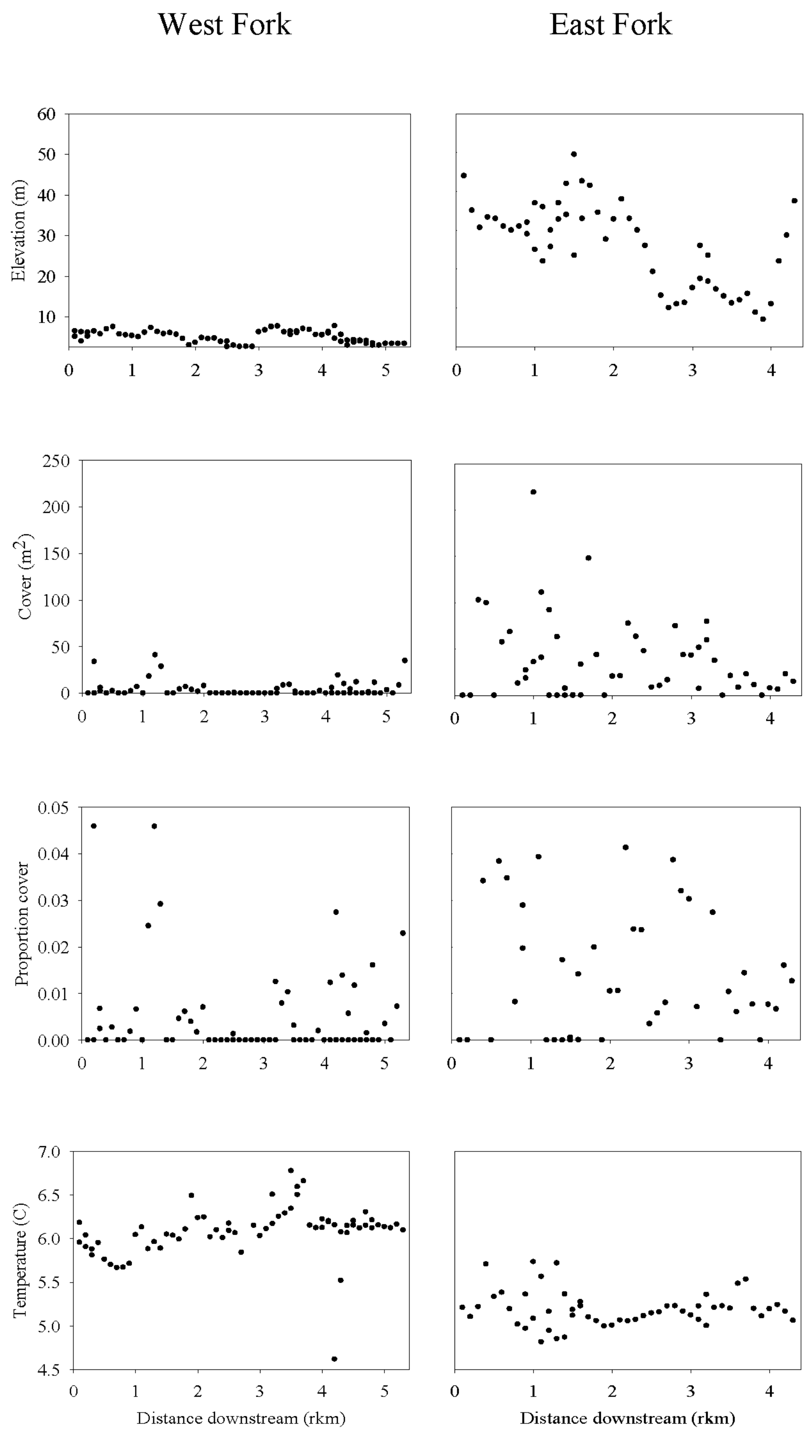

Figure 3.5 Elevation, cover area, proportion cover, and temperature from upstream to downstream in both study areas of the Kulukak River.

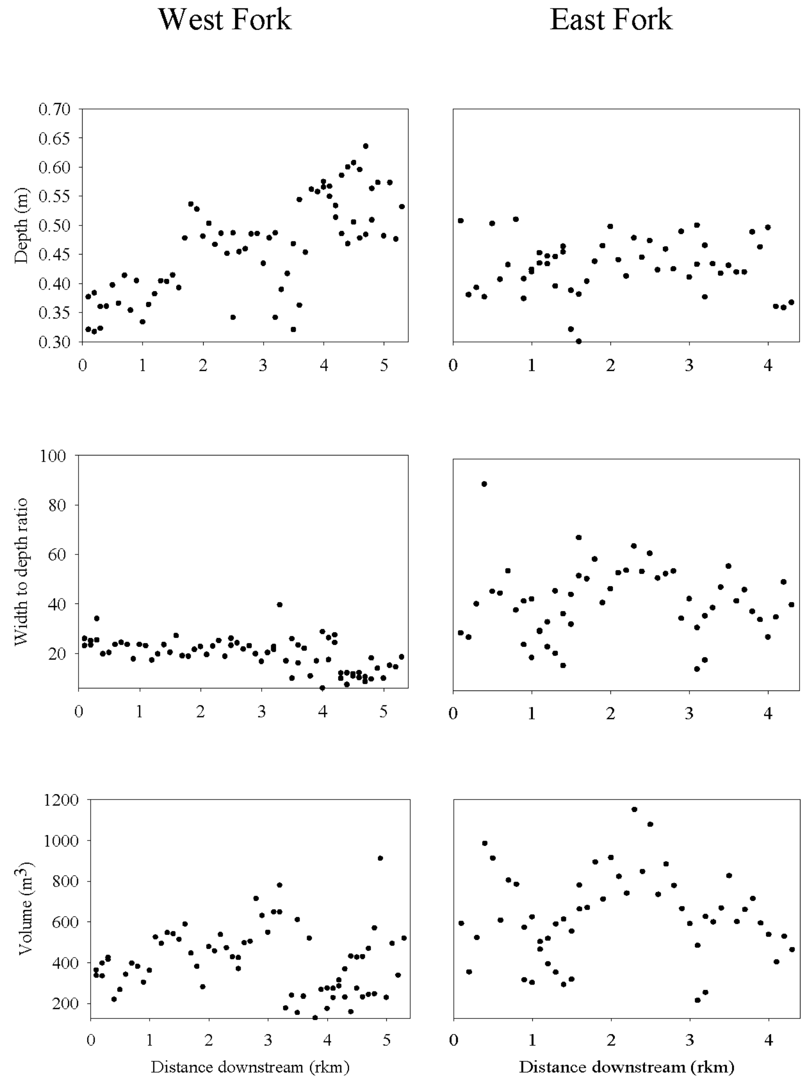

Figure 3.6 Depth, width-to-depth ratio, and volume from upstream to downstream in both study areas of the Kulukak River.

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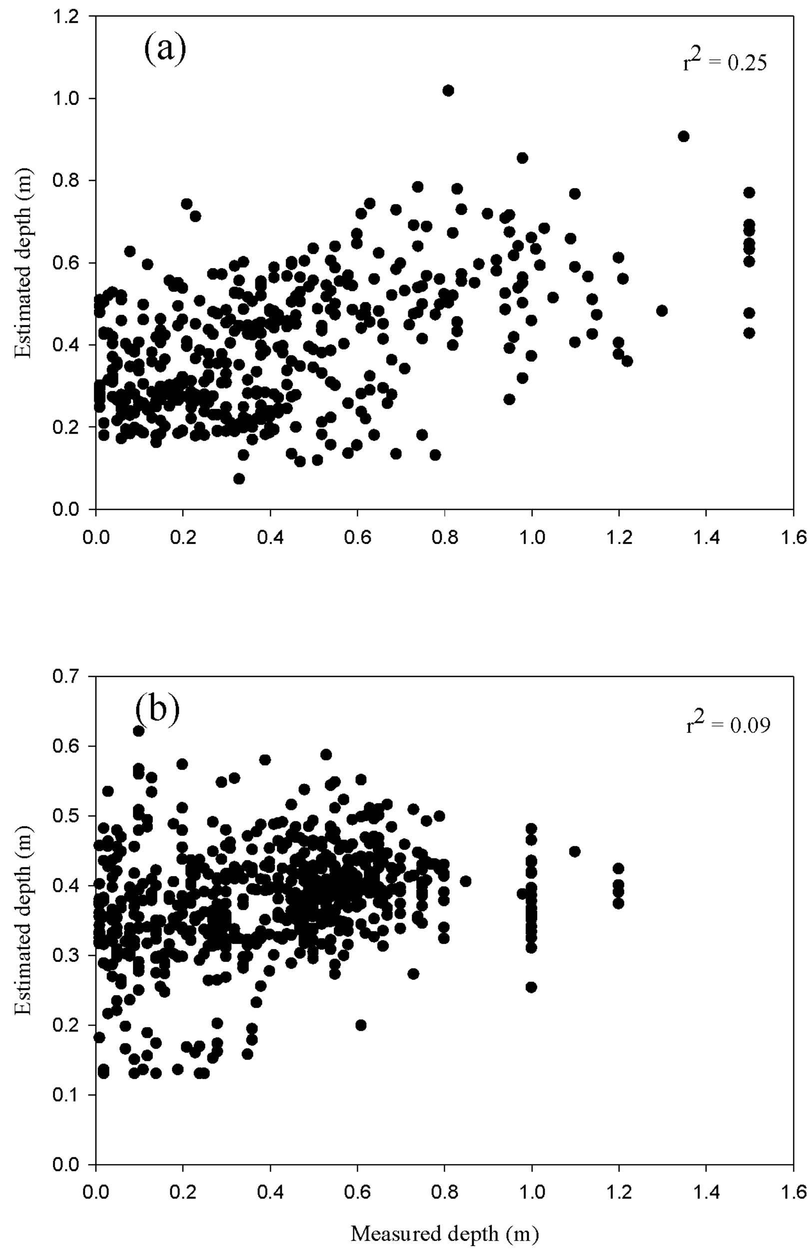

Figure 3.7 Depth (as measured in the field) versus estimated depth measurements for the West (a) and East (b) Fork of the Kulukak River.

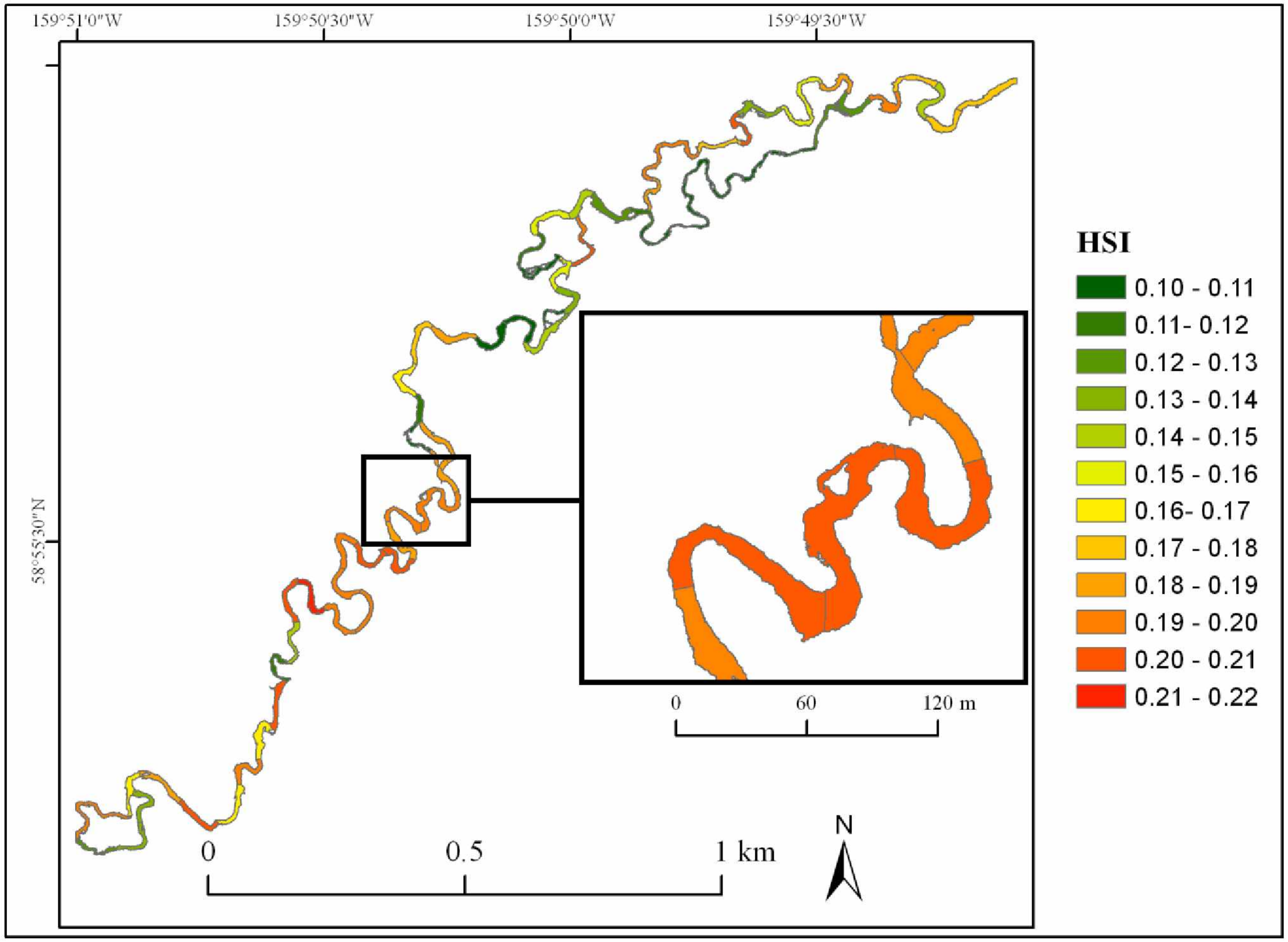

Figure 3.8 Minimum habitat-suitability indices for all reaches in the West Fork study area.

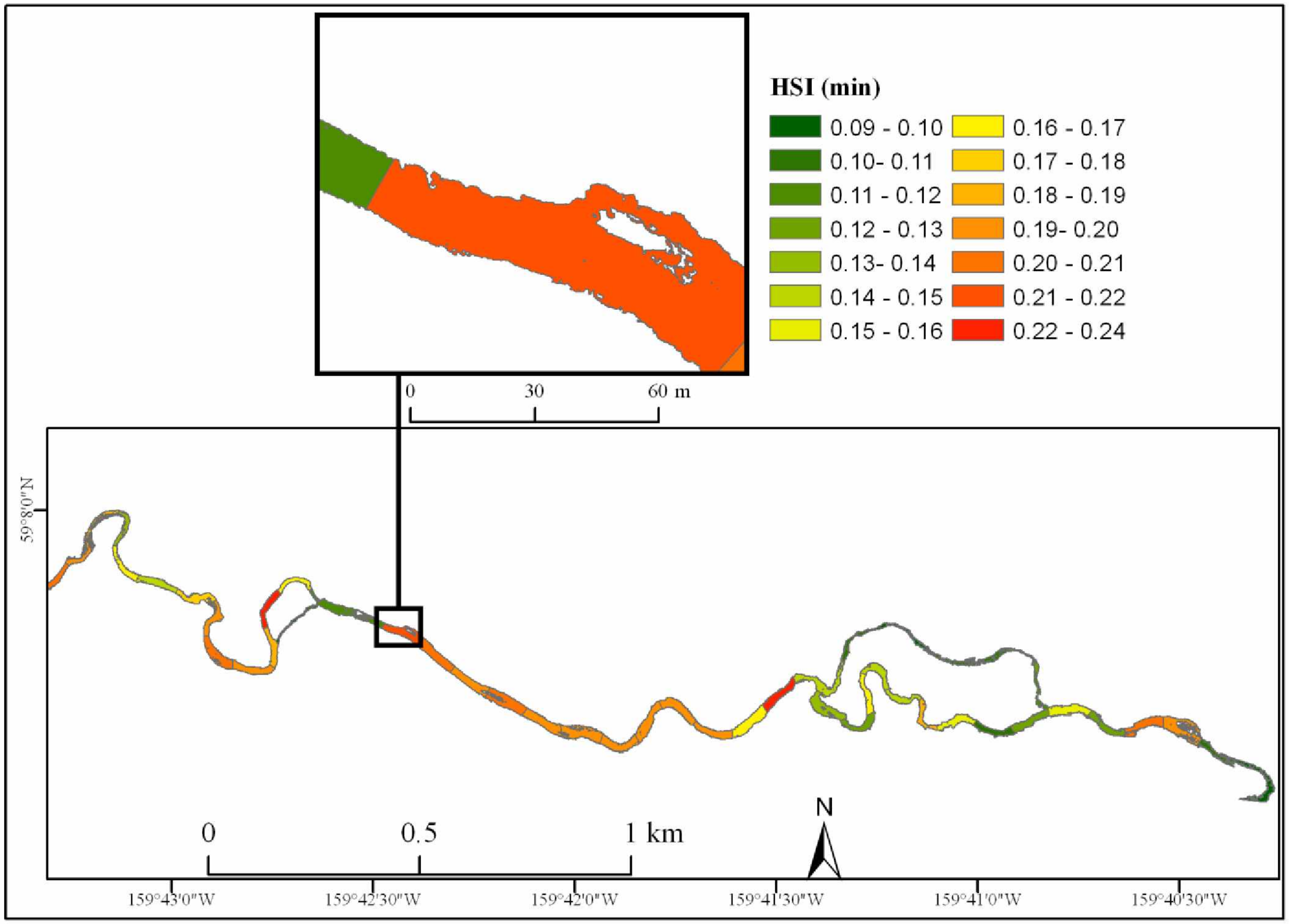

Figure 3.9 Minimum habitat-suitability indices for all reaches in the East Fork study area.

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Chapter 4: General conclusions

4.1 Study summary

The first objective of this study was to develop methods for classifying and mapping juvenile Pacific salmon *Oncorhychus* spp. rearing habitat using multispectral aerial photography. I demonstrated that a decision-based fusion of aerial photographs collected in the visible (VIS), near infrared (NIR), and thermal infrared (TIR) portion of the electromagnetic spectrum can accurately classify eight distinct in-stream and landcover classes important to mapping and describing juvenile salmon habitat in shallow (<1m) streams. Overall accuracy of the shallow West Fork study area was found to be 82.5%, a value slightly lower than the 85% accuracies suggested by some in the remote-sensing community as acceptable for use (Foody 2002). This is, on average, higher other similar multispectral studies (Wright et al. 2000; Puestow et al. 2001; Legleiter et al. 2002; Whited et al. 2002a; Whited et al. 2002b; Leckie et al. 2005; Gilvear et al. 2007b), but lower than those using hyperspectral systems (Marcus 2002; Marcus et al. 2003). The fact that the VIS bands are useful for classifying in-stream habitat is supported by the fact that these bands penetrate water surfaces (Lillesand et al. 2004), but the need to include NIR bands for improved classification of similar classes is supported by similar studies that use hyper- and multi-spectral systems (Wright et al. 2000; Puestow et al. 2001; Legleiter et al. 2002; Marcus 2002; Whited et al. 2002a; Whited et al. 2002b; Marcus et al. 2003; Leckie et al. 2005; Gilvear et al. 2007b). Unique to this study is the demonstrated ability of a TIR band to extract off-channel eddy drop zone (EDZ)/backwater areas, habitat that is important to juvenile salmon rearing (e.g., Nickelson et al. 1992a; Pollock et al. 2004), but has not previously been mapped using aerial photography.

The evaluation of these techniques reveals several limitations to and recommendations for using multispectral aerial imagery for classifying habitat-unit types. Classification of the East Fork study area, which was deeper than the West Fork study area, produced an accuracy of only 67.5%. This low accuracy can be attributed to the inability of light to penetrate deep into water, a problem that has been recognized in other riverine aerial photography studies (Winterbottom and Gilvear 1997; Gilvear et al. 2007a). In addition, differential between-image illumination was a problem in this particular study area, and in general can lead to misclassification issues for aerial photography (Lillesand et al. 2004). This verifies the importance of taking imagery on completely clear or completely cloudy days. Misclassification errors can also be attributed to the subjectivity associated with mapping discrete habitat types, an issue for which fuzzy logic may serve as an effective alternative (Legleiter and Goodchild 2005). Coregistration between image sources was not only time-intensive, but most likely resulted in misclassifications. For this problem, it is recommended that a true multispectral or hyperspectral system be used instead of three separate cameras. Finally, it is acknowledged that methods and accuracy estimates may be seasonally dependent, and validation during different times of year is essential if temporally continuous data is sought.

The second objective was to use these developed techniques to quantify habitat variables often used in juvenile salmon rearing studies in order to characterize two study areas on the Kulukak River. From the classified images, I was able to enumerate number and area of habitat-unit types, two variables that are often used to estimate and sample freshwater fish (Hankin and Reeves 1988) and specifically juvenile salmon (Nickelson 1998). Further, I was able to estimate various other variables often used in habitat surveys on the study area, reach, and pixel scale, and create spatially-explicit maps of habitat type, temperature, and water depth. Finally, I demonstrated that this information can be used to create spatially-explicit habitat-suitability maps and determine overall habitat suitability, using coho salmon *O. kisutch*, as an example. The West Fork study area was more sinuous and contained a higher percentage of slow-moving habitat including EDZ/backwater areas, habitat types that have been found to support high densities of coho, sockeye *O. nerka*, and Chinook *O. tshawytscha* salmon in these study areas (J. Coleman, UAF, unpublished data) and elsewhere (McMahon 1983; Hillman et al. 1987; Murphy et al. 1989; Reeves et al. 1989; Nickelson et al. 1992a; Nickelson 1998; Rosenfeld et al. 2000; Sharma and Hilborn 2001; Anderson and Hetrick 2004; Pollock et al. 2004). The East Fork study area, however, contained a higher percentage of cover than the West Fork, a feature important for creating juvenile salmon rearing habitat (Bjornn and Reiser 1991). The East Fork also featured a large quantity of run habitat, which may be used more by Chinook salmon than by coho and sockeye salmon (Hillman et al. 1987; Murphy et al. 1989; Holecek et al. 2009). Overall habitat-suitability indices suggest that neither study area is very suitable for juvenile salmon rearing, and that both are limited by pool density and cover. Electrofishing estimates of different habitat types conducted during a concurrent study in these study areas supports this (J. Coleman, UAF, unpublished data), with density estimates for juvenile coho salmon by habitat type on average lower than those suggested by researchers (Nickelson 1998) and those found in other rivers in southwestern Alaska (Anderson and Hetrick 2004).

Although the quantification of habitat variables in these two study areas using aerial imagery and GIS-based techniques demonstrates the potential of these techniques to improve juvenile salmon habitat models and monitoring, several aspects of these techniques need validation and improvement. First, application of these methods and assessment of their accuracy over different seasons would give a clearer picture of potential limiting habitat. Formal validation of the quantification of cover, an investigation into the relationship between landcover classes and undercut bank prevalence, and an attempt to separate LWD from other cover classes would complement and strengthen this approach, as cover is potentially very important to monitoring juvenile salmon habitat (Bjornn and Reiser 1991). Spatially continuous maps of depth, although believed to demonstrate relative water depth in shallow sections of water, produced low R^2 values. Several studies have shown that depth can be more reliably mapped in shallow streams (Winterbottom and Gilvear 1997; Gilvear et al. 2007a) than demonstrated in this study, and thus improvements such as unbiased field sampling, constant illumination conditions, better coregistration, histogram matching, and/or a hyperspectral system may increase accuracy of depth mapping. Finally, an important next step in developing spatially explicit juvenile salmon habitat maps is to collect spatially-explicit juvenile salmon abundance data, which would greatly improve juvenile salmon habitat models and prediction capabilities.

4.2 Scalability

As discussed previously, there are many limitations to these specific remote-sensing based techniques. Although accuracy and efficiency of these methods may be improved through the aforementioned recommendations on equipment, processing and classification techniques, and field data collection, some variables may remain undetectable through remote-sensing approaches, and other remain unknowable. However, if the ultimate goal of these methods is to efficiently monitor changes in fish populations over large spatial and temporal scales, a major potential limitation that needs to be considered is the scalability of these techniques.

One of the limitations of expanding the fine-scale (i.e., habitat-unit scale) methods discussed in this study to a large spatial area is the difficulty and time-consuming nature of the image pre-processing, most notably the mosaicing and georeferencing. Due to the inherent distortions in aerial photography due to factors such as camera tilt, uneven topography, and general aerial perspective, it is highly unlikely that even a few images will mosaic perfectly with each other. The likelihood of this occurrence decreases with increasing numbers of photos and more topographically complex areas (Lillesand et al. 2004). Although there is software available for automated photogrammetry, mosaicing, and georeferencing, there will always be a significant amount of manual manipulation involved in these techniques. Although it is possible that images be acquired from higher elevations and at lower resolutions to classify the same habitat features, is has been shown that accuracies decrease with lower resolutions (Legleiter et al. 2002). Increasing these methods to larger areas may also be problematic due to differences in habitat and geomorphology between sites, even within the same watershed. As mentioned previously, these specific methods are not appropriate for larger streams or systems that have significant amounts of cover. In addition, streams with differing water chemistry and/or sediment load would require unique training sets, if not completely new classification methods, to classify using remote-sensing methods.

The problem of increasing the amount of spatial areas covered is compounded by increasing the temporal scale. As juvenile Pacific salmon often change habitat use seasonally (e.g., Nickelson et al. 1992a) and experience different habitat limitations during different seasons (Quinn 2005), it may be necessary to collect data at various times during the year. As noted earlier, it is unclear whether these specific methods are seasonally dependent, and seasonal monitoring may require new technique development. If true long-term change needs to be monitored and detected, many years worth of data is desired (Larsen et al. 2004). In summary, a larger temporal scale increases data, but increases time and cost spent in processing those data.

Even if these exact methodologies cannot be expanded to huge spatial and/or temporal scales, they are necessary to determine relevant relationships that will further improve the efficiency of monitoring juvenile salmon habitat. By monitoring these habitats through remote-sensing techniques while collecting relevant fish data in these same habitats, researchers will be able to determine which fish-habitat relationships are most important. As a result, these researchers will be able to expand monitoring of only the most relevant variables to larger scales. Monitoring of these fine-scale habitats through these techniques in conjunction with larger-scale variables, such as topography, water flow, and climate, may yield other important correlations. For example, sinuosity, gradient, and water flow have all been shown to affect habitat type, quantity, and distribution (Rosgen and Silvey 1996). Because this type of data can be collected at coarser resolutions, it may serve as the most efficient solution to monitoring juvenile salmon populations. In the end, it will be up to researchers and managers to determine the data needs, the time and cost constraints, and which scales provides the best balance between the two tradeoffs.

4.3 Implications

The methods in both chapters 2 and 3 illustrate that habitat that supports juvenile Pacific salmon can be mapped and quantified using multispectral aerial photography and GIS-based methods. Mapping and quantifying juvenile Pacific Salmon habitat using watershed (Bradford et al. 1997; Sharma and Hilborn 2001; Burnett et al. 2007), reach (e.g., Hillman et al. 1987; McMahon and Hartman 1989; Quinn and Peterson 1996; Ebersole et al. 2003; Ebersole et al. 2009), micro-habitat (Bisson et al. 1988; Taylor 1988; McMahon and Hartman 1989; Bjornn and Reiser 1991; Beecher et al. 2002), and habitat-unit (e.g., Nickelson et al. 1992b; Nickelson and Lawson 1998; Anderson and

Hetrick 2004; Nemeth et al. 2004; Anderson 2007) scale variables have all been used to explore habitat-juvenile salmon relationships. Further, these habitat variables have been used to predict juvenile salmon densities, explore habitat preferences, and estimate carrying capacity (Fausch et al. 1988). Unfortunately, collecting this type of data on spatial and temporal scales simultaneously large enough and detailed enough to be useful for management purposes using traditional field-based methods is very difficult and expensive (Fausch et al. 2002), and potentially also subjective (Al-Chokhachy and Roper 2010). By using remote sensing and GIS-based methods, researchers have the opportunity to collect multi-scale data that is potentially low-cost, efficient, and a source for objective analysis approaches.

The importance of developing new, low-cost methods for monitoring fish habitat, and thus fish populations is clear. With the increased interest in both life-history and ecosystem-based approaches to salmon management (e.g., Nickelson and Lawson 1998; Sharma and Hilborn 2001; Scheuerell et al. 2006) and the threat of climate-driven and human-induced changes to freshwater habitats available to Pacific salmon during the spawning and rearing life stages (Regier and Meisner 1990; Northcote 1992; Bradford and Irvine 2000; Battin et al. 2007; Ficke et al. 2007), cataloging, assessing, and monitoring the quality and quantity of available rearing habitat will continue to be important objective for many management agencies involved in managing and conserving salmon stocks (Larsen et al. 2004). These new cost effective, spatially-continuous, and effective monitoring methods will allow researchers and managers new tools in fish habitat monitoring, and thus better means of conserving and managing stock of Pacific salmon.

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Appendix A: Assessing thematic accuracy of classified maps

The most widely accepted method of representing thematic accuracy in the remote-sensing community in recent decades is the error matrix (Congalton and Green 1998). Use and publication of the results of an error matrix was first popularized in the late 1980s. This technique is described in detail in Congalton and Green (1998), which provides the basis for this appendix.

Early in the history of formal thematic accuracy assessments, a simple estimate of the overall accuracy of classification techniques was presented. Overall accuracy was produced by comparing sample areas on the classified map with the corresponding areas on the reference data, which could be generated in a variety of ways, including ground observation. However, in any case, this approach was considered to be correct. In order to compute this single value, one would simply have to record the number of times that the classified map and the reference data were in agreement.

Eventually, it became evident that there was a need to evaluate individual categories within the classification process at which point the error matrix began to be widely used. The error matrix is a square array of numbers that expresses the number of pixels (or other sample units) assigned to a particular class in one classification relative to the number of pixels assigned to a particular class in another classification. Usually, one of these classifications is the reference data, and thus considered correct. Table A 1 is an example of an error matrix, taken from my accuracy assessment of the West Fork of the Kulukak River study area mosaic. In this table, the columns represent the pixels that are classified as particular classes according to the reference data, whereas the rows represent the pixels that are classified as particular class according to the classified map.

Examining an error matrix is an effective way of understanding map accuracy because individual accuracies of each category are illustrated, as well as errors of inclusion (commission errors) and errors of exclusion (omission errors). A commission error is including an area in a class when it does not belong in that class, whereas an omission error is excluding an areas from the class to which it belongs. Every error is simultaneously an omission error from the correct class and a commission error to the incorrect class. For example, in Table A 1, there are two pixels that were, according to reference data, riffles that were classified as run pixels. Therefore, two pixels were omitted from the correct riffle class and committed to the incorrect run category.

In addition to demonstrating specific commission and omission errors, various measures of accuracies can be computed from the error matrix. As discussed earlier, the overall accuracy is the proportion of times that the reference data and classified maps are in agreement; thus, one can compute an overall accuracy by summing the long diagonal of the error matrix and dividing by the total number of pixels sampled, as illustrated in Table A 1. User's and producer's accuracies were first introduced by Story and Congalton (1986) and are measures representing individual category accuracies. User's accuracies represent the proportion of a particular class that is correctly classified according to reference data, whereas the producer's accuracy is the proportion of a particular class in the reference data that is correctly classified. If I was interested in the ability to classify the riffle class, I could calculate the producer's accuracy for this class by dividing the total number of pixels correctly classified as riffles (26) by the total number of pixels that are actually riffles (30). As demonstrated in Table A 1, this would give a producer's accuracy of 86.6%, which would be considered high. However, to conclude from this result that these methods effectively represent true proportions of riffles would be erroneous. I could also calculate the user's accuracy of this class by dividing the number of pixels correctly classified as riffles (26) by the total number of pixels classified as riffles (50), resulting in a much lower value of 52.0%. In other words, 86.6% of riffles have been classified as riffles, but only 52.0% of the riffles on the map are actually riffles. Thus, the producer of the map can claim that 86.6% of the riffles are illustrated correctly on the map, whereas the user of the map will find that only 52.0% of the time the riffles on the map are correctly identified.

Table A 1. An error matrix example, taken from the accuracy assessment of the classification of the West Fork of the Kulukak River study area mosaic.

Classified Pixels	Reference pixels								
	Riffle	Pool	Run	EDZ/ backwater	Gravel	Wood	Grass	Ice	Total
Riffle	**26**	0	2	11	1	10	0	0	50
Pool	0	**50**	0	0	0	0	0	0	50
Run	2	9	**36**	3	0	0	0	0	50
EDZ	2	1	7	**40**	0	0	0	0	50
Gravel	0	0	0	0	**29**	19	1	1	50
Wood	0	0	0	0	0	**50**	0	0	50
Grass	0	0	0	0	0	1	**49**	0	50
Ice	0	0	0	0	0	0	0	**50**	50
Total	30	60	45	54	30	80	50	51	**400**

Overall accuracy = (26+50+36+40+29+50+49+50)/400 = 82.5%

<u>Producer's accuracy</u>	<u>User's accuracy</u>
Riffle = 26/30 = 86.6%	Riffle=26/50 = 52.0%
Pool = 50/60 =83.3%	Pool = 50/50 = 100.0%
Run = 36/45 = 80.0%	Run = 36/50 = 72.0%
EDZ = 40/54 = 74.1%	EDZ = 40/50 = 80.0%
Gravel = 29/30 = 96.6%	Gravel = 29/50 = 58.0%
Wood = 50/80 = 62.5%	Wood = 50/50 = 100.0%
Grass = 49/50 = 98.0%	Grass = 49/50 = 98.0%
Ice = 50/51 = 98.0%	Ice = 50/50 = 100.0%

References

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Appendix B: Spatially continuous maps

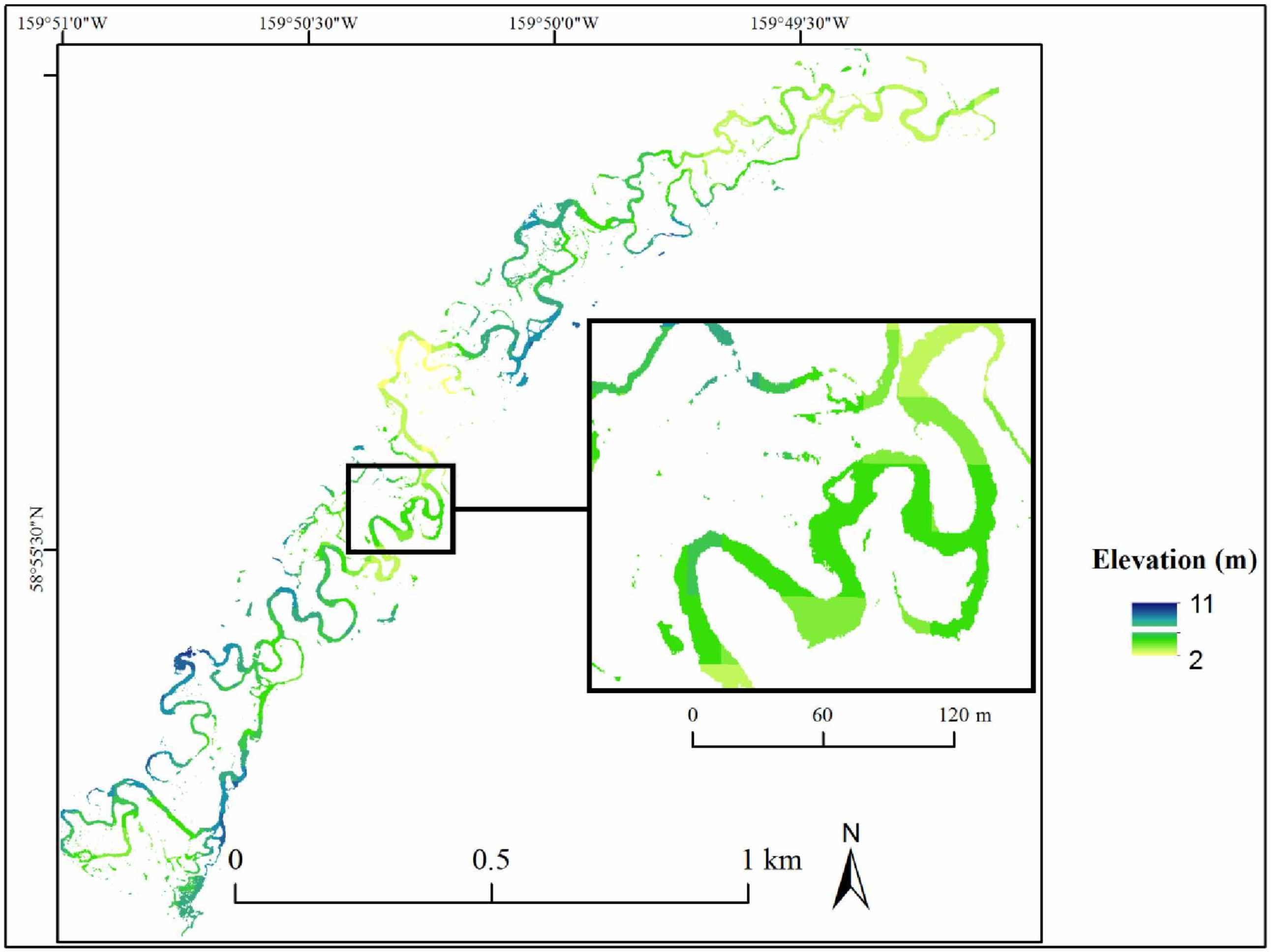

Figure B 1 Elevation values for the West Fork study area.

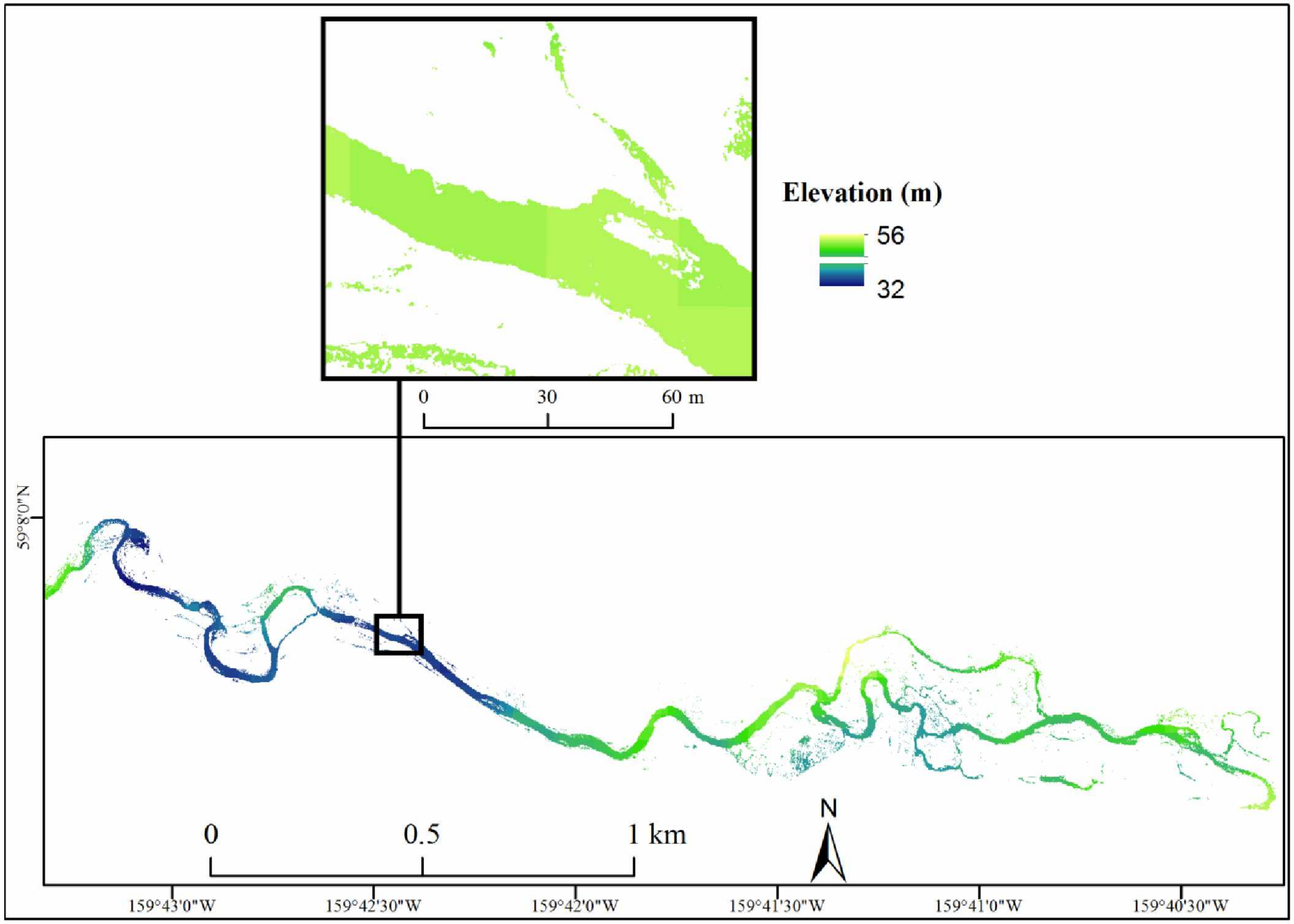

Figure B 2 Elevation values for the East Fork study area.

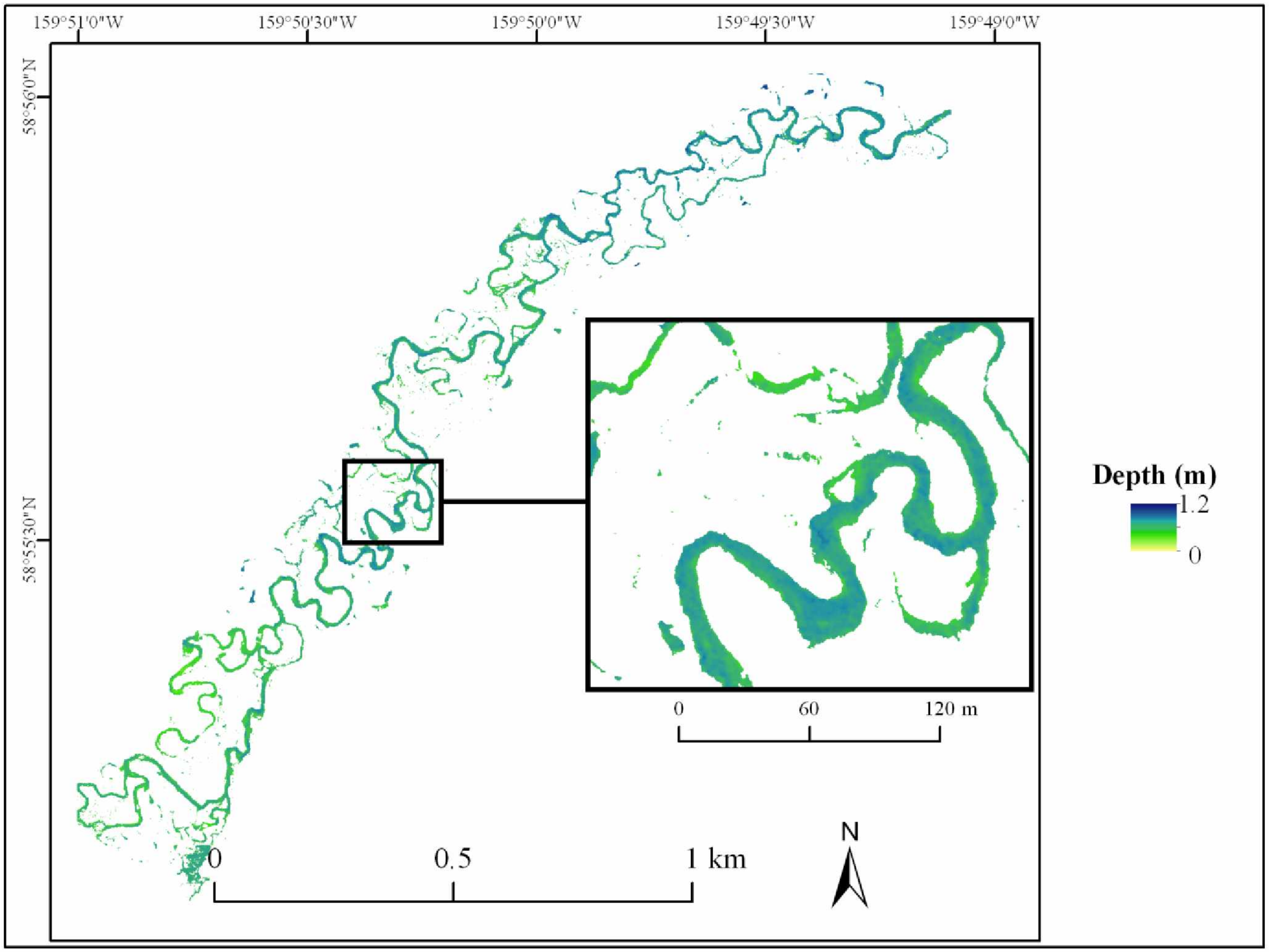

Figure B 3 Depth values for the West Fork study area.

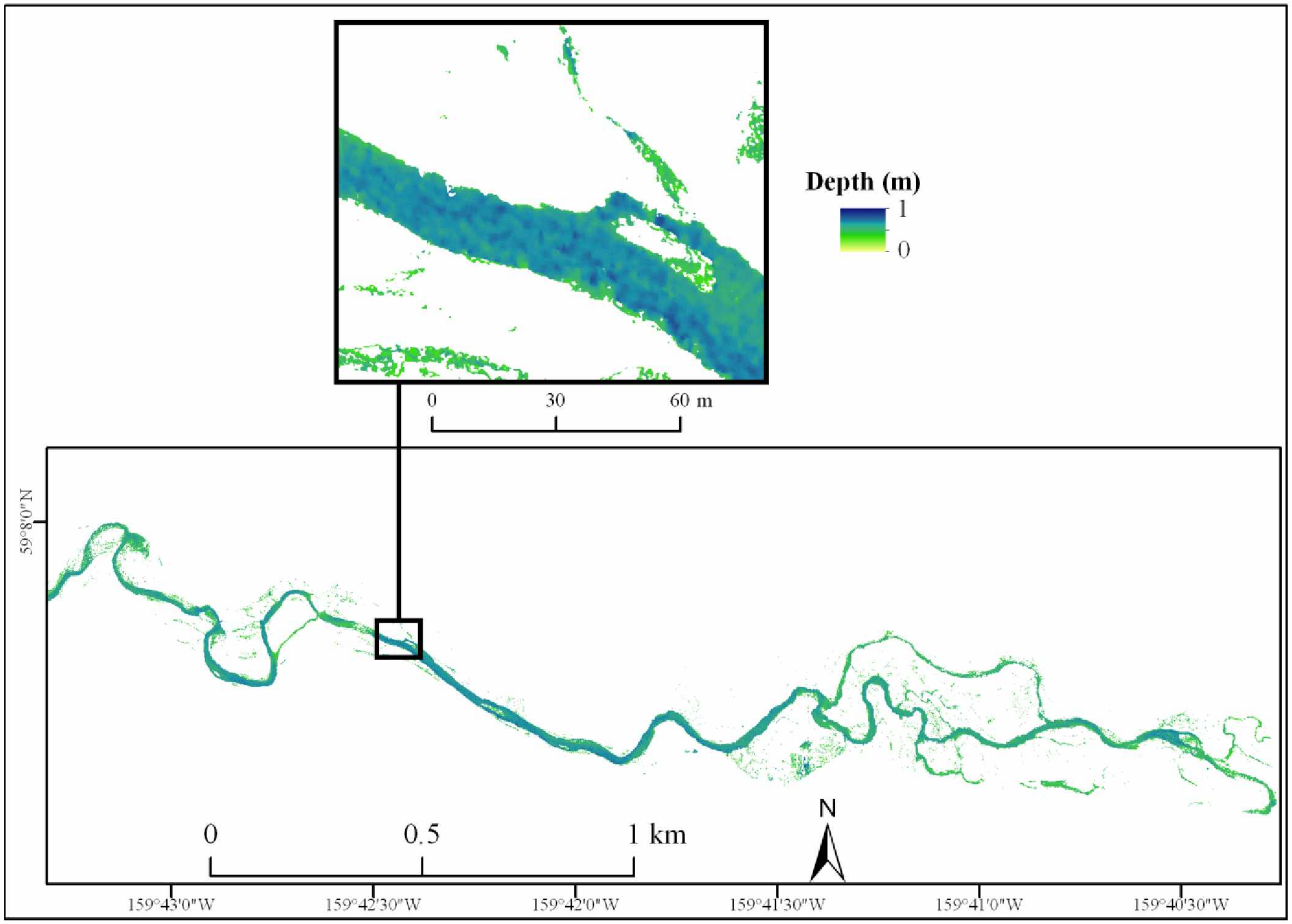

Figure B 4 Depth values for the East Fork study area.

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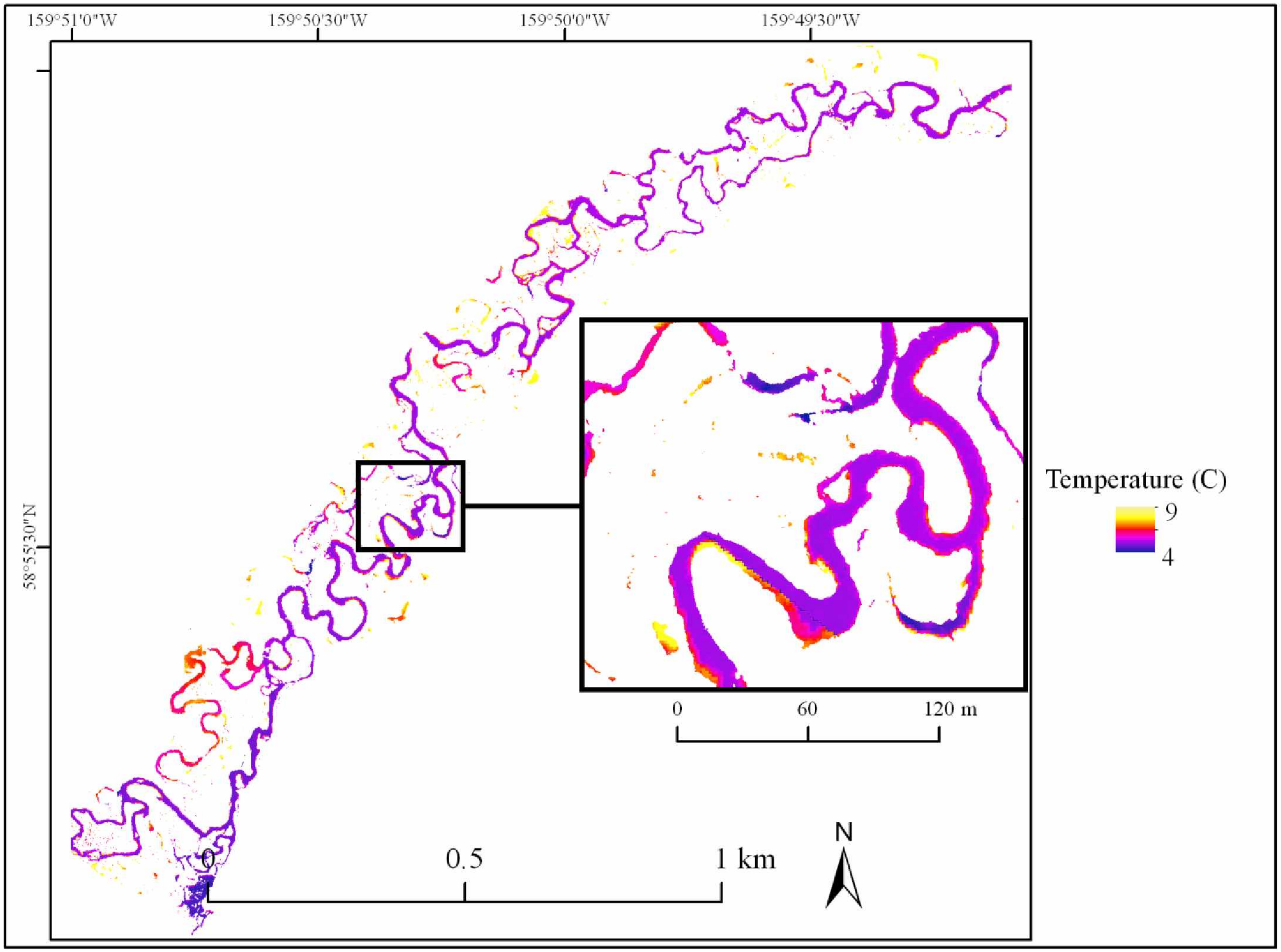

Figure B 5 Temperature values for the West Fork study area.

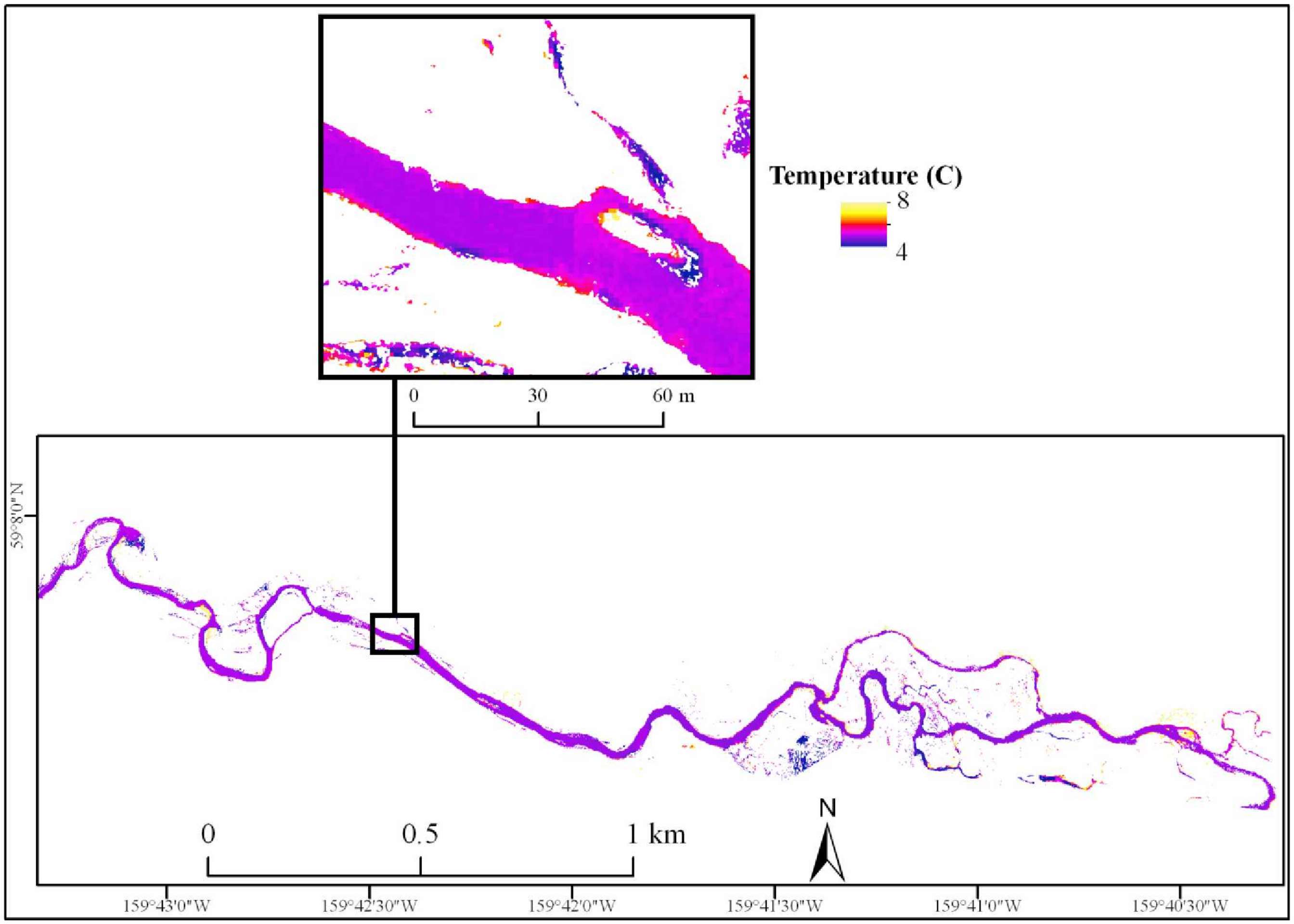

Figure B 6 Temperature values for the East Fork study area.